THREE ESSAYS IN FINANCIAL ECONOMICS

BY

YONGJUN KIM

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Doctoral Committee:

Professor Timothy C. Johnson, Chair, Director of Research
Professor Neil Pearson
Professor Heitor Almeida
Assistant Professor Jaewon Choi

ABSTRACT

The first essay, Wage Differentials, Firm Investment, and Stock Returns, investigates the effects of labor costs on firms' capital investments and stock returns. I estimate wage premia across U.S. industries and show that the negative investment-return relation implied by q-theory is steeper for high wage firms than for low wage firms. Using wage premia as a proxy for labor adjustment costs, an extended investment-based model predicts the interaction effect because capital-labor complementarity implies that labor market friction also governs the investment decision. The inflexibility induced by wages offers new insights into asset prices and corporate investments.

In the second essay, Anomalies in the Joint Cross Section of Equity and Corporate Bond Returns, we show that many cross-sectional anomalies in equity returns do not appear in the corporate bond returns of the same firms. These puzzling findings are in fact consistent with contingent claim pricing. Corporate bonds typically have low credit risk and their hedge ratios, or the sensitivity of debt to equity, are quite small. As a result, much less than 10% of equity return premia translate to corresponding bond return premia. Exceptions are asset growth, investment, and momentum, in which bond return premia are too large compared with hedge ratios, suggesting that the bond return premia are driven by channels that function independently of changes in underlying firm values. We also document the investor sentiment effect in corporate bonds by showing that expected returns on bond portfolios hedged against equity risk increase with sentiment and are concentrated on the short side of long-short strategies.

The third essay, Labor Skills and Technology Change, highlights the importance of labor characteristics for firm behavior and asset prices. The productivity of skilled labor is subjected to aggregate technology innovation, implying that a firm's usage of skilled labor determines its exposure to the shock. I find that profits are more sensitive to technology shocks in firms depend more on skilled worker. Combined with the positive price of technology risk, high skill firms have higher expected returns than low skill firms.

To my family, for their love and support.

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CHAPTER 1

WAGE DIFFERENTIALS, FIRM INVESTMENT, AND STOCK RETURNS

1.1 Introduction

One of the anomalies in the U.S. labor market is the persistent wage differentials across industries, which refers to the phenomenon that equivalent workers (in terms of socioeconomic characteristics) earn different wages when employed in different industries.[1] For example, a worker may earn 30% more in the automobile industry than in apparel production. These wage differentials are persistent and, hence, cannot be attributed to transitory disequilibria. However, the source of wage differentials across industries is still unclear. The literature has pointed out that the difference is governed by exogenous industry characteristics rather than firm characteristics or unobservable worker ability.[2] Among the explanations offered, several studies argue about the importance of labor adjustment costs as the determinant of relative wages.[3] This argument results in the intuition that firms in high wage industries behave as if their physical capital is very costly to adjust because physical capital and labor are complements in production.[4]

The cost associated with adjustments is the key feature in the q-theory of investment framework. With these costs, investment and labor hiring are forward-looking variables that contain information on future discount rates. Firms invest (hire) more when the net present value of new investment (hiring) is high, or when the cost of capital is low. This negative covariance between investment and cost of capital is the cornerstone of the q-theory of investment, which has been shown to have the power to explain cross-sectional patterns. If labor becomes costlier to adjust, the same level

[1]See, for example, Krueger and Summers (1987), Katz and Summers (1989), and Thaler (1989) for early evidence. See also Caju et al. (2010) for evidence from eight EU countries.

[2]Dickens and Katz (1987) show that industry fixed effects explain a significant portion of individual wage variations, and Blackburn and Neumark (1992) find that only one-tenth of the variation in differentials reflects differences in unobserved ability.

[3]See, for example, Lang (1991), and Montgomery (1991) for an explanation using search theory, Bulow and Summers (1986) for an explanation based on the worker monitoring problem, and Stiglitz (1974), Salop (1979), and Krueger and Summers (1988) for an explanation based on the labor turnover model. In particular, Krueger and Summers (1988) document evidence against the hypothesis that high wages compensate for the difference from (1) the undesirable aspects of working conditions or (2) the treats from collective bargaining. The relationship between wage and labor adjustment costs is also investigated in empirical studies. See, for example, Hamermesh (1993) for a comprehensive survey of labor adjustment costs and Dube et al. (2010) for recent evidence on employee replacement costs.

[4]The capital-labor complementarity is based on empirical estimates from micro data of the elasticity of substitution between capital and labor. See Chirinko (2008) for a comprehensive survey of the elasticity of substitution.

of labor hiring incurs higher costs, making the hiring decision less elastic to changes in the cost of capital. Costly labor creates an incentive to postpone investments even when the cost of capital is low enough because capital-labor complementarity implies that labor market frictions also govern investment decisions. In other words, investments by high wage firms should be less elastic to changes in the cost of capital than investments by low wage firms.

To test this prediction, I estimate the industry wage premia that account for the differences in wages of equally skilled workers across industries. Industry wage premia represent the excess wage after compensating for observable characteristics, such as age, skill, and occupation. Consistent with the literature, I find persistent differences in wage premia across industries. For example, industries that paid high wage premia in 1980 (e.g., railroads, postal service) also paid high wage premia in 2010. The persistence of wage premia is more pronounced for industries paying low wage premia. More importantly, in the data, the estimated wage premia show a positive relation with proxies for labor adjustment costs, which supports the labor adjustment cost explanation of wage differentials.

I start by investigating the response of investment to changes in opportunities to further motivate the inflexibility effect induced by wages. The procyclicality of investments is a well-known stylized fact in the literature. Because adjustment costs determine the speed of adjustment, high wage firms may tend to delay capital expenditures if wages involve changes in flexibility. Consistent with the intuition, I find an inelastic capital adjustment or less cyclical investments for high wage industries. My baseline estimates imply that a one-standard-deviation increase in wages is associated with a 0.27% lower increase in investments given a typical increase in the productivity shock (proxied by the real GDP growth rate).

I then confirm the main asset pricing prediction that investments in high wage industries are less elastic to changes in the cost of capital. From the two-way portfolio sorts on wage premia and investment, I find that the investment spread is larger for high wage industries in both magnitude and significance. For example, when the investment-to-assets ratio is being proxied for a firm's capital investment, the average equal-weighted investment monthly spreads are -0.81% and -1.11% for low and high wage portfolios, respectively. The gap between two spreads holds after controlling for Fama-French risk factors. Similar patterns are found for other investment proxies that are widely used in the literature.

The difference in investment spreads between wage groups is a robust feature of the data. In a cross-sectional Fama-MacBeth regression framework, a one-standard-deviation increase in wage premia is associated with a 0.24% greater decrease in subsequent returns for a typical increase in the investment-to-assets ratio. The relation holds after controlling for other predictors, such as size, book-to-market, momentum, and reversal. The marginal wage effect is insignificant, suggesting that the wage only changes the slope of the investment-return sensitivity.

I explore additional asset pricing implications of wage differentials. Labor hiring is also known to be a forward-looking variable, where the effect of wages is more direct. Using number of employees as a proxy for firm labor input, I find that firms in high wage industries have steeper hiring-return spreads than low wage industries, similar to capital investments. The role of operating inflexibility on the value premium has received significant attention in the recent literature.[5] Because expanding (contracting) capital corresponds to an increase (decrease) in the labor input, it becomes costlier to adjust capital when firm pays high wage premia, suggesting that value firms in high wage industries are riskier than growth firms. Indeed, I find that the value spread (measured using the CAPM model) of high wage industries is approximately 50% larger in terms of magnitude than that of low wage industries.

To check the robustness of the main prediction, I revisit the main cross-sectional tests using wage premia estimates from the March Current Population Survey (March CPS) that is published annually. One concern regarding census data is a lower data frequency relative to the March CPS. However, the March CPS does not contain as many observations as the census, which may bias the estimation results. I compare wage premia estimates from two datasets and find that those from the March CPS are not severely biased. More importantly, the cross-sectional results using the March CPS deliver exactly the same message as in the main tests.

To interpret the link between asset prices and labor costs, I consider the neoclassical investment-based model proposed by Belo et al. (2014). In the model, managers make hiring and investment decisions to maximize firm value, taking the stochastic discount factor as a given to value cash flows. The key feature of the model is labor adjustment costs, which are designed to capture the fact that hiring and firing workers is not costless. In this setup, I offer a set of quantitative demonstrations of the theoretical model to support the empirical findings.

This study contributes to the recent advances in asset pricing research on the labor sector.[6] Specifically, the approach in this study is mostly related to the investment-based asset pricing literature motivated from the q-theory of investment. Belo et al. (2014) develop a labor-augmented investment-based model to explain the negative hiring-return relation in the cross-section. Belo et al. (2016) further document that the negative hiring-return relation is steeper for firms that depend more on skilled workers using the evidence that adjusting skilled workers is costlier than adjusting unskilled workers. In this study, the source of friction is drawn from the persistent difference in industry wage premia, a proxy for labor adjustment cost that represent excess wages after accounting for compensation for observable characteristics including labor skill. I show the consequences of inter-industry wage differentials for investment, labor hiring, and the cost of capital, thus providing comprehensive implications of labor costs in the neoclassical investment-based model framework.

In this regard, this study adds to a large body of empirical literature on the predictability of firm investments to the cross-section of stock returns. The negative relation between investments and stock returns has been explained by either the q-theory of investment (e.g., Cochrane (1991,

[5]See, for example, Carlson et al. (2004), Zhang (2005), and Cooper (2006).

[6]See Danthine and Donaldson (2002), Merz and Yashiv (2007), Chen and Zhang (2011), Petrosky-Nadeau et al. (2017), Favilukis and Lin (2016), and Hall (2017) for an analysis at the aggregate level. See also Chen et al. (2011), Eisfeldt and Papanikolaou (2013), Belo et al. (2014), Donangelo (2014), Ochoa (2015), Belo et al. (2016), Donangelo et al. (2016), Kuehn et al. (2016), and Zhang (2016) for an analysis at the firm level.

1996), Li et al. (2006), and Liu et al. (2009)) or behavioral forces, such as investor misperceptions (e.g., Titman et al. (2004), Cooper et al. (2008)). In this debate, Li and Zhang (2010) document the failure of the q-theory of investment for the hypothesis that firms with high investment friction have strong investment-return sensitivity.[7] Contrary to Li and Zhang (2010), my results provide supportive evidence for the rational theories of the investment effect in the cross-section.

This study also contributes to the literature on labor economics. Among the numerous previous studies regarding industry wage differentials, it is surprising that most studies focus only on the determinants of the differentials and not on their consequences. Borjas and Ramey (2000) document evidence that industries with high initial wage premia experienced lower employment and productivity growth in subsequent years. Shim and Yang (2017) show that high wage industries experience more evident job polarization. In addition to aggregate outcomes, I show the consequence of wage differentials at the firm level.

The remainder of this paper is organized as follows. In Section 1.2, I describe the database used in this study and present wage premia estimation results. Section 1.3 presents the empirical findings. In Section 1.4, I offer theoretical explanations of the results. Section 1.5 concludes.

1.2 Data

1.2.1 Database

The key variable in the empirical analysis is industry wage premia, a proxy for labor adjustment cost and representing excess wages after accounting for compensation for observable characteristics. I calculate wage premia across industries using: (1) decennial Census and American Community Survey (ACS) data and (2) the March Current Population Survey (March CPS).[8] The census data extract, as of the census year, a 1% or 5% random sample of all working persons who do not live in group quarters. The ACS is the successor to the census' long-form questionnaire, which was retired after the 2000 census. The ACS collected detailed demographic data from a subset of census respondents. As in Acemoglu and Autor (2011), the relatively large sample size of the census data makes fine-grained analysis within detailed demographic groups possible. Following Acemoglu and Autor (2011), I use 1% of the U.S. population in 1960 and 1970 and 5% of the population in 1980, 1990, and 2000. From 2006 and beyond, I use the ACS data that contain a 5% population sample.

As an alternative database, one can consider the March Current Population Survey (CPS) to estimate wage premia. The CPS is a monthly U.S. household survey conducted jointly by the U.S. Census Bureau and the Bureau of Labor Statistics to measure unemployment after the Great Depression. Over time, supplemental inquiries on special topics were added for particular months. Among these surveys, the March CPS provides data on the labor force, employment, hours of work,

[7] They consider measures of firm-level financing constraints as a proxy for investment friction.

[8] Data were extracted from the Integrated Public Use Microdata Series (IPUMS) website: http://www.ipums.org/ (Ruggles et al. (2015) and Flood et al. (2015)).

earnings, and other demographic characteristics. One advantage of using March CPS is that it is published annually, whereas the census is published once in a decade. However, the March CPS provides smaller samples than the census, potentially resulting in noisy estimates. Because wage premia across industries persist for decades, I use the census and ACS data as the main databases for the analysis.[9] I obtain firms' stock information from the Center for Research in Security Prices (CRSP) and accounting information from the Compustat Annual Industrial Files.

1.2.2 Industry Wage Premia

Using the aforementioned data, I estimate industry wage premia from a sample that includes persons employed in wage-and-salary sectors and restrict the age range to 16-64. I classify U.S. non-agricultural industries into 60 categories using Census Industry Codes (CIC) in IPUMS data, as shown in Appendix B.[10] I regress the following model separately in each census year, similar to Borjas and Ramey (2000):

$$log(Wage_{h,i,t}) = X_{h,i,t}\beta_t + \omega_{i,t} + \epsilon_{h,i,t}, \tag{1.1}$$

where $Wage_{h,i,t}$ is the wage rate of worker h in industry i in census year t; X is a vector socioeconomic characteristics; and ω is an industry fixed effect or industry wage premia.[11] The vector X controls for the worker's age (indicating whether a worker is 18-24, 25-34, 35-44, 45-54, or 55-64), educational attainment (indicating whether the worker has less than 9 years of schooling, 9 to 11 years, 12 years, 13-15 years, or at least 16 years), race (indicating whether the worker is black), sex (female or male), region of residence (indicating in which of the nine census regions the worker lives), and occupation (at the one-digit level).

Table 1.1 provides the estimation results. I only report the 10 highest and lowest wage industries in 1980 and 2010. It is apparent that industries that paid high or low in 1980 also paid similarly in 2010. For example, railroad industries paid the highest wage premia in 1980 and the second highest in 2010. Industries newly entered into the top 10, such as chemical products industries, ranked 13th in 1980. Some industries experienced a drastic change in wage premia during the period. The legal service industry ranked 32nd in 1980 but was marked as the sixth highest wage industry in 2010. The persistence of wage premia seems more pronounced among low wage industries.

Figure 1.1 graphically shows wage premia persistence across all 60 industries. In Figure 1.1, I compare estimated wage premia in 1980 and 2010 for all 60 industries. I also run a simple regression of industry wage premia in 2010 on the premia estimated in 1980. The estimated slope coefficient is 0.98, indicating a clear pattern of persistence. In summary, the estimation results presented in

[9] The main cross-sectional tests using the March CPS are presented in Appendix C.

[10] I drop agricultural and related industries following Krueger and Summers (1988) because a large fraction of workers in the agricultural industry is self-employed.

[11] The dummy for "Hotels and lodging places" is omitted in the specification. Its wage premia is always set equal to zero.

this section not only confirm the results of previous studies but find that the phenomenon persists into the 2010s.

I investigate whether the estimated wage premia is associated with other labor characteristics. Table 1.2 provides the time-series average of the correlation between labor characteristics. Unions make wages sticky and layoffs costlier, thus reducing operating flexibility. I find that wage premia is positively correlated with labor unionization, which may support the argument of Nickell and Wadhwani (1990).[12] It is well known in the literature that skilled labor is costly to adjust. I find a moderate positive correlation with labor skills.[13] Neumuller (2015) present an endogenous relation between labor mobility and industry wage differentials in a competitive labor market framework, suggesting that two characteristics are negatively related. However, I find a low but positive correlation between wage premia and labor mobility.[14] Lastly, I obtain correlations with the labor hiring variable. All else being equal, high labor costs increase the investment (hiring) threshold, thereby decreasing the level of investment (hiring). This statement implies a negative correlation between wage and hiring, which is consistent with Borjas and Ramey (2000).

Although the assumption that wage premia are proxies for labor adjustment costs is guided by the literature, I support the assumption from the data. As in Ochoa (2015), I exploit firm-level data from the 1980 Employer Opportunity Pilot Project (EOPP), a unique employee-employer matched data set containing information on approximately 5,200 firms from ten different states in the United States and different industries. The data contain detailed information on new hires' socioeconomic characteristics, including age, gender, and education level. It also contains information on the costs related to hire new employees. I consider three proxies of labor adjustment costs: the amount of time the employer and other staff spent recruiting, screening and interviewing the new hire ($Screening$), the amount of time employees and supervisory staff spent training the new hire ($Training$), and the last new hire productivity gap ($Productivity\ Gap$) defined as the productivity of the last employee in the position relative to the productivity of the new employee during the second week of employment. It should be noted that the measures do not fully represent the adjustment costs dimensions because these proxies do not contain the costs related to firing workers.

In Table 1.3, I report the OLS estimation results. Specifically, I regress the hiring cost measures on wage premia estimated in (1.1). I also consider several worker characteristics (Age, $Male$, and $Skill$) and establishment size ($Size$) as control variables. In all specifications considered, I find a

[12] Union data at the industry-level are from www.unionstats.com. See Hirsch and Macpherson (2003) for details.

[13] I define labor skill measure at the industry level each year, which is the fraction of high skilled workers in a given industry. I classify skilled labor at the occupation level using the Dictionary of Occupational Titles (DOT): Revised Fourth Edition, 1991 from the U.S. Department of Labor. DOT includes information on Specific Vocational Preparation (SVP), which measures the amount of lapsed time required by a typical worker to learn the techniques, acquire the information, and develop the facility needed for average performance in a specific job-worker situation. The value of SVP ranges from 1 to 9, where SVP = 1 corresponds to the lowest preparation, and SVP = 9 corresponds to the highest preparation over 10 years. I define a high skill occupation if its SVP index is equal to or greater than 7 (corresponding to an occupation that requires more than two years of preparation) and low skill otherwise. Using SVP numbers, I measure industry skill intensity by calculating the percentage of skilled workers in the industry. The data on the number of workers by occupation in each industry are from the Bureau of Labor Statistics, Occupational Employment Statistics (OES) program.

[14] I thank Andres Donangelo for kindly sharing the labor mobility data used in Donangelo (2014).

positive relation between wage premia and labor adjustment costs. For example, a one-standard-deviation increase in wage premia (0.23) is associated with 0.59 more hours on screening, 2.64 more hours on training, and 1.21% wider productivity gaps. The results show the positive relation between wage premia and labor adjustment costs, validating the inflexibility assumption.

1.2.3 Sample

My main firm-level sample is drawn from the intersection of CRSP and the Compustat Annual Industrial Files from 1967 to 2014. Following the cross-sectional asset pricing literature, firms in financial (SIC codes 6000-6999) and regulated industries (SIC codes 4900-4999) are excluded. I also exclude firms with missing book asset values, size measures, and book-to-market ratios. To avoid the results driven by microcap firms discussed in Fama and French (2008c), I follow Donangelo (2014) and exclude firms in the lowest 20th size quantile. I match fiscal year-end accounting information in year t-1 with stock return data from July of year t to June of year t+1 to ensure that the accounting information is fully incorporated into stock returns, following Fama and French (1992).

Throughout the study, I employ three capital investment measures for the empirical analysis. The first investment measure is investment-to-assets ($IA1$) following Lyandres et al. (2008). Motivated by the q-theory of investment, it is defined as the change in gross property, plant, and equipment (Compustat item PPEGT) plus the change in inventories (item INVT) divided by lagged total assets (item AT). Property, plant, and equipment rep- resent long-lived operational assets, such as buildings, machinery, and other equipment. Inventories represent short-lived assets, such as merchandise, raw materials, and work in progress. The second measure, asset growth ($IA2$) following Cooper et al. (2008), is measured as the change in total assets (Compustat item AT) divided by lagged total assets, which is a comprehensive measure of firm investment (Fama and French (2015), Hou et al. (2015)). I also use capital expenditures (Compustat item CAPX) divided by property, plant, and equipment (item PPENT) as the last investment measure ($IA3$), which is used widely in the literature.

I keep track of the following variables. Firm hiring ($Hire$) is defined as the change in the number of employees (Compustat item EMP) divided by the lagged number of employees, similar to Bloom (2009).[15] Firm size ($Size$) is the log market value of equity from CRSP. The book-to-market ratio (BM) is defined following Fama and French (1993). The measure of firm profitability (ROA) is operating income before depreciation (Compustat item OIBDP) divided by lagged total assets (item AT). Firm leverage ($Mkt.\ Lev$) is total book debt (Compustat item DLC+DLTT) divided by the sum of book debt and the market value of equity.

[15] As noted in Belo et al. (2014), it is important to understand the limitations to using number of employees as a proxy for firm labor input. There is no distinction between full-time, part-time, and seasonal workers. Moreover, labor input in the production function should be adjusted for hours worked, which is not the case for the hiring variable in the model context. For these reasons, my main focus is not on the interpretation of hiring, although labor input is a forward-looking variable.

In Table 1.4, I report summary statistics for the sample used in the empirical analysis. Specifically, I form two portfolios sorted on wage premia using information available in June of each year. For each portfolio, I calculate the time-series average of the cross-sectional median portfolio characteristics. I separately report the statistics of low wage firms (Panel A) and high wage firms (Panel B). The purpose of wage sorting is to understand firm characteristics in different wage industries. Table 1.4 shows that firms paying high wage premia are on average larger, have lower book-to-market ratios, and have lower profitability-although the differences are not notably significant relative to the difference in wages. The average of the investment ($IA1$, $IA2$, and $IA3$) and hiring ($Hire$) variables are slightly lower for high wage portfolios, consistent with the negative correlation shown in Table 1.2.

I further sort firms into two decile portfolios using wage premia and investment ($IA1$). In each wage group, it is clear that firms with high investments tend to have higher hiring rates, indicating that both variables are highly correlated. On average, high investment firms are larger than low investment firms, but the relation is not monotonic. Consistent with the findings in the literature, a high investment is negatively associated with the book-to-market ratio and positively correlated with profitability.

1.3 Empirical Results

1.3.1 Aggregate Shock and Corporate Investment

The inflexibility hypothesis suggests that high wage industries should be less responsive than low wage industries to changes in opportunities, when all else is equal. Before presenting the asset pricing results, I test the cyclicality of firm investments across different wage industries to motivate the inflexibility effect induced by labor costs. Recent work by Kim and Kung (2017) show how firm investments react to economic uncertainty through the asset redeployability channel, which proxies for capital adjustment costs. Similar to their approach, I consider a pooled OLS regression of the form:

$$IA_{i,t+1} = a_i + \beta_1 * Shock_{t+1} + \beta_2 * Wage_{i,t} + \beta_3(Shock_{t+1} * Wage_{i,t}) + ctrls_{i,t} + \epsilon_{i,t+1}. \quad (1.2)$$

The dependent variables are the three investment variables ($IA1$, $IA2$, and $IA3$) and the labor hiring variable ($Hire$) used throughout this study. If a firm adjusts its labor force in a manner similar to capital, the same prediction should apply to labor hiring. For this reason, I consider labor hiring as a dependent variable. The real GDP growth rate is employed as a proxy for the time-varying aggregate productivity shock ($Shock$). To estimate the response of investments to aggregate shocks, I interact $Shock$ and the wage premia variable ($Wage$). If a positive productivity shock corresponds to an increase in firm investments on average, the model's prediction suggests that the interaction term ($Shock * Wage$) is negative, implying that low wage firms invest more than high wage firms in response to positive shocks. In the specification, to control for time-varying investment opportunities at the firm-level, I include several proxies, such as $Tobin's\ q$, $Cash\ Flow$, and cash holding ($Cash$). a_i denotes firm fixed effects. All standard errors are clustered at the firm level.

Table 1.5 shows the estimation results of (1.2). In column (1), where $IA1$ is used as a dependent variable, it is clear that firms on average increase investments when positive productivity shocks occur. The coefficient estimate on $Shock$ (0.005) implies that a one-standard-deviation increase in GDP growth (2.1) corresponds to an average 1% increase in investments. As predicted, high wage firms increase investments less than low wage firms in response to productivity shocks. In column (2), the coefficient on $Shock * Wage$ is an estimated -0.01, implying that a typical increase in GDP growth is associated with a 0.27% lower increase in investments for a one-standard-deviation increase (0.27) in wages. Columns (3) to (6) employ different capital investment measures ($IA2$ and $IA3$). The estimated coefficient of $Shock * Wage$ is -0.02 in column (4) and -0.023 in column (6), which provide the same message as in the results based on $IA1$. A similar pattern is found in a firm's labor force adjustment. The estimated coefficient on $Shock * Wage$ is -0.006 (column (8)), implying that a typical increase in GDP growth is associated with a 0.16% less increase in labor hiring for a one-standard-deviation increase in wage premia.

I aggregate firm-level variables into industry-level variables and repeat the analysis shown in Table 1.6. Using the industry classification described in Appendix B, I calculate the industry-level $Tobin's\ q$, $Cash\ Flow$, $Cash$, and leverage.[16] Similar to previous firm-level analysis, investments in the high wage industry are less elastic to changes in productivity shocks. In contrast to the positive $Shock$ coefficients, I find $Shock * Wage$ to be significantly negative in all specifications considered. The economic magnitude is also significant. In column (2), when $IA1$ is proxied for capital investment, a typical increase in GDP is associated with a 0.4% lower increase in investments for a one-standard-deviation increase in wages. However, the interaction term is negative but not significant for labor hiring (column (8)). In all, the results indicate an inelastic adjustment of high wage industries to aggregate economic change.

1.3.2 Cross-sectional Analysis

1.3.2.1 Portfolio Analysis

If high wages dampen the response of investments to changes in opportunities, then it is natural to expect investments to be inelastic to changes in the cost of capital for high wage firms, resulting in a steeper investment-return relation. To test the hypothesis, I employ the portfolio approach to investigate the interaction effect of wages and investments in the cross-section. I first sort firms

[16] For each year, I calculate the sum of all available firm-level items to obtain industry-level items. I then calculate industry-level variables used in the analysis.

into decile portfolios according to their investment level in June of each year t using information available at the end of the previous year. The purpose of this analysis is to replicate the negative investment-return relation regardless of the wage premia. I form both equal- and value-weighted portfolios of monthly stock returns from July of year t to June of year $t+1$, and the portfolios are rebalanced in June of each year.

Table 1.7 provides the excess returns and abnormal returns measured by the Fama-French three factor model for decile portfolios sorted on three investment variables. Consistent with previous studies, I find a significant investment effect in the cross-section of stock returns. For example, in Panel A with sorts on $IA1$, the average monthly high-minus-low returns are -0.99% when equal-weighted. They are highly statistically significant at the 1% level with an absolute t-statistic value higher than 8. The investment spread is not subsumed by additional risk factors, such as the Fama-French three factor model. I find a similar strong investment effect in the value-weighted portfolio results, although both the magnitude and the significance are smaller than that for the equal-weighted results.

The portfolios sorted on $IA2$ exhibit results similar to the $IA1$ results. For example, the average monthly equal-weighted investment spread measured by the three factor model is -0.88% with significance at the 1% level when equal-weighted. However, when returns are value-weighted, the asset growth effect weakens, consistent with Fama and French (2008c). Although I find highly significant excess returns for high-minus-low returns, the three factor alphas are marginally significant. The cross-sectional pattern for $IA3$ is mostly similar to $IA2$ patterns. Overall, I confirm the well-known empirical results in the literature that high investment firms earn subsequent lower returns.

My main hypothesis is that the investment-return relation is steeper for high wage industries because high wages and labor adjustment costs make firm investments inelastic to changes in the cost of capital. To investigate the interaction effect, I form two decile portfolios double sorted on wage premia and investment, as follows. At the end of June of each year, firms are sorted into two wage portfolios using the industry wage premia. Meanwhile, firms are independently grouped into ten investment portfolios using the NYSE breakpoints in the previous year. I form both equal- and value-weighted portfolios of monthly stock returns, and the portfolios are rebalanced in June of each year.

Table 1.8 documents the excess returns and Fama-French three factor alphas for the wage-investment portfolios. I only report low, high, and high-low investment portfolios in each wage bin. In Panel A, I report equal-weighted portfolio results sorted on three investment variables. As predicted, the magnitude of the investment spread is larger for high wage industries than for low wage industries. For example, the average high-minus-low equal-weighted excess returns are -0.81% and -1.11% for the low and high wage portfolios, respectively. Moreover, the difference in the two spreads is statistically significant at the 1% or 5% level. The same patterns are found for the $IA2$ and $IA3$ results. In particular, for $IA3$, the high-minus-low three factor alphas of high wage industries are twice as large as those of low wage industries.

The value-weighted portfolio results are qualitatively similar albeit weakly statistically significant. In Panel B, the average high-minus-low excess returns are -0.52% and -0.67%, respectively, for the low and high wage portfolios when $IA1$ is a sorting variable. When the three factor model is used to obtain alphas, the high-minus-low alphas are -0.29% and -0.54%, showing larger gaps between wage groups. The result is interesting when compared with the one-way sort results in Table 1.7 because the $IA1$ effect is mostly driven by high wage industries, although the one-way sort result shows the unconditional existence of the effect.

The results based on $IA2$ or $IA3$ deliver the same message. When $IA2$ is a sorting variable, the value-weighted high-minus-low excess returns are -0.40% and -0.57%, respectively, for the low and high wage portfolios. More importantly, the investment spread is significantly negative only for high wage industries when abnormal returns are used. The results are weak when $IA3$ is used as a sorting variable. I find significant high-minus-low returns only for high wage industries. However, the investment spreads measured by Fama-French alphas are not significant for both low and high wage portfolios.

To summarize, the results show that not only is capital investment priced in the cross-section of stock returns but also that the effect significantly depends on labor costs. I find a strong investment-return sensitivity for high wage industries. The interpretation from q-theory is that investments by high wage firms are less elastic to changes in the cost of capital than investments by low wage firms.

1.3.2.2 Fama-MacBeth Regressions

The results based on portfolio sorts in the previous section do not control for other characteristics that might affect stock returns. In this section, I employ the standard Fama-MacBeth regression approach to control for other firm-level characteristics using the following model:

$$R_{i,t+1} = \alpha_t + \delta_t * IA_{i,t} + \gamma_t * Wage_{i,t} + \lambda_t(IA_{i,t} * Wage_{i,t}) + ctrls_{i,t} + \epsilon_{i,t+1}. \tag{1.3}$$

In addition to three investment measures and wage premia, I include several explanatory variables known to predict stock returns.[17] I consider firm size ($Size$), the logarithm of book-to-market ratio ($log(bm)$), past 12-month stock return skipping the most recent month ($R^E_{2,12}$), past 1 month stock return (R^E_1), labor hiring ($Hire$), idiosyncratic risk ($Idiosyn$), market leverage ($Mkt.Lev$), and cash flow ($Cash\ Flow$).[18] The variable of interest is the interaction term between investment and wage premia ($IA*Wage$), where $Wage$ is the wage premia estimated in equation (1.1). The steeper investment-return relation for high wage firms implies a negative coefficient on the interaction term.

Table 1.9 documents the Fama-MacBeth regression results for excess stock returns. In columns

[17] Firm-level variables in the regressions are winsorized at the top and bottom 1% to reduce the influence of outliers.

[18] Many empirical studies suggest anomalies driven by systematic mispricing that arise from the limit-to-arbitrage. To proxy for mispricing in each stock, I exploit the idiosyncratic risk measure defined as the logistic transformation of the coefficient of determination from a regression of daily excess returns on the Fama-French three factor model, following Ferreira and Laux (2007).

(1) to (3), I report the estimation results when investment-to-assets ($IA1$) is used as the main investment variable. In column (1), I find a strong negative relation between IA and returns. More importantly, I find the variable of interest $IA * Wage$-the interaction between investment and wage premia-to be significantly negative. This coefficient clearly indicates a steeper investment-return relation for high wage industries, corroborating the hypothesis in a regression setting. The marginal wage effect is insignificant, suggesting that the wage only changes the slope of the investment-return sensitivity. The results are robust to controls. For example, the estimate for $IA * Wage$ is -1.114 after controlling for size, book-to-market, momentum, and reversal, which is significant in terms of economic magnitude. For a typical increase in investments, a one-standard-deviation increase in wage premia (0.27) is associated with a 0.3% greater decline in subsequent returns. In column (3), I further include labor hiring, idiosyncratic risk, leverage, and cash flow as controls. Still, the investment-wage interaction term is estimated at the 1% significance level.

I report the estimation results when asset growth ($IA2$) (columns (4) to (6)) or capital expenditures ($IA3$) (columns (7) to (9)) is used as the main investment variable. The results are very similar to those of $IA1$. The variable of interest, $IA * Wage$, is significant and large in magnitude for all specifications considered. Combined with the portfolio results, I present a strong investment-wage interaction effect in the cross-section of stock returns.

1.3.2.3 Hiring Spread

As in Belo et al. (2014), labor hiring is a forward-looking variable, similar to capital investments. Throughout this study, the focus has been on the response of capital investments to labor market friction based on capital-labor complementarity. Obtaining accurate firm-level labor input is also empirically challenging. Despite the difficulties, Belo et al. (2014) document the negative hiring-return relation, and Belo et al. (2016) further show that the relation is steeper for industries using skilled labor based on the costly adjustment of skilled labor. Because wage involves a change in labor adjustment costs, it is natural to ask whether high wage industries have a steeper hiring-return relation than low wage industries.

In Table 1.10, I report the average returns for the decile hiring portfolios (Panel A) and two decile portfolios sorted on wage premia and labor hiring (Panel B).[19] In the decile portfolio sorting (Panel A), I confirm the negative hiring-return relationship in the cross-section, although it becomes weak when returns are value-weighted. In Panel B, when returns are equal-weighted, it is apparent that high-minus-low portfolio returns for high wage portfolios are larger in magnitude than low wage portfolios. The monthly high-minus-low return is -0.49% for low wage industries and -0.88% for high wage industries. They are also statistically different at the 1% level. I find a similar pattern when Fama-French alphas are used to construct portfolio returns.

In the value-weighted results in Panel B, I find a relatively weaker hiring-return relation for two wage portfolios. The hiring spread shows statistical significance for high wage industries but not

[19] The sorting procedures are similar to those in Table 1.7 and Table 1.8.

for low wage industries. In contrast, I find no significant spreads for two wage portfolios when abnormal returns are used, although they differ at the 10% level. In all, the results suggest that high wage industries have a steeper hiring spread, as anticipated.

1.4 Theoretical Explanation

1.4.1 Setup

To interpret the empirical evidence presented in the previous section, I exploit a multi-period neoclassical investment model proposed by Belo et al. (2014). In the model, the firm uses capital K_t and labor inputs N_t to produce output Y_t with the following constant elasticity of substitution (CES) technology,

$$Y_t = Z_t X_t^{1-\theta}[\alpha K_t^{1-1/\phi} + (1-\alpha)N_t^{1-1/\phi}]^{\theta/(1-1/\phi)}, \tag{1.4}$$

where $\alpha > 0$ indicates the relative weight of the two inputs in the production process, $0 < \theta \leq 1$ is the degree of returns to scale, and the parameter $\phi > 0$ is the elasticity of substitution between physical capital and the labor stock. The term X_t is aggregate productivity and Z_t is firm-specific productivity, which is the source of cross-sectional firm heterogeneity.

The law of motion of the firm's capital (K_t) and labor force (N_t) are,

$$\begin{aligned} K_{t+1} &= (1-\delta_k)K_t + I_t,\ 0 < \delta_k < 1 \\ N_{t+1} &= (1-\delta_n)N_t + H_t,\ 0 < \delta_n < 1, \end{aligned} \tag{1.5}$$

where δ_k, δ_n are depreciation and the worker quit rate, respectively. I_t is capital investment and H_t is gross hiring, both of which can be positive (e.g., investment) or negative (e.g., disinvestment).

Both capital investment and labor hiring are also subjected to convex and non-convex adjustment costs, similar to Merz and Yashiv (2007). Capital and labor adjustment costs are specified by the following function,

$$Adj_t^K = I_t + \begin{cases} b_k^+ Y_t + \frac{c_k^+}{2}(\frac{I_t}{K_t})^2 K_t & \text{if } I_t > 0 \\ 0 & \text{if } I_t = 0 \\ b_k^- Y_t + \frac{c_k^-}{2}(\frac{I_t}{K_t})^2 K_t & \text{if } I_t < 0, \end{cases} \tag{1.6}$$

$$Adj_t^N = \begin{cases} b_n^+ Y_t + \frac{c_n^+}{2}(\frac{H_t}{N_t})^2 N_t & \text{if } H_t > 0 \\ 0 & \text{if } H_t = 0 \\ b_n^- Y_t + \frac{c_n^-}{2}(\frac{H_t}{N_t})^2 N_t & \text{if } H_t < 0, \end{cases} \tag{1.7}$$

in which b_k^+, b_n^+, b_k^-, $b_n^-, c_k^+, c_n^+, c_k^-$, and c_n^- are constants. Capital adjustment costs include planning and installation costs, learning the use of equipment, and costs related to temporal interrupted operation. Labor adjustment costs include worker training and screening, advertising job positions, and separation costs. Non-convex costs capture the costs of adjustments independent of the size of the investment or hiring, where convex costs capture the fact that adjustment costs are related to the degree of adjustment. The model allows capital and labor adjustment costs to be asymmetric to capture the concept that the costs of investment (hiring) and disinvestment (firing) can differ.

The key aspect of the model is that adjustment costs are stochastic. Let Adj_t be the total factor adjustment costs,

$$Adj_t = \frac{Adj_t^K + Adj_t^N}{S_t}, \tag{1.8}$$

where S_t is a stochastic adjustment cost shock. This shock affects the marginal cost of investment (hiring) and disinvestment (firing).[20] Lastly, there are fixed costs in the firm's production process that are the same across firms.

1.4.2 Stochastic Process

The aggregate productivity follows a stationary Markov transition function,

$$\Delta x_{t+1} = \mu_x + \sigma_x \epsilon_{t+1}^x, \tag{1.9}$$

in which $x_{t+1} = log(X_{t+1})$ and ϵ_{t+1}^x is an i.i.d. standard normal shock. μ_x denotes the average growth rate of aggregate productivity and σ_x indicates conditional volatility of the process. Firm are also subjected to the firm-specific productivity which has a distribution,

$$z_{t+1} = \bar{z}(1 - \rho_z) + \rho_z z_t + \sigma_z \epsilon_{t+1}^z, \tag{1.10}$$

in which $z_{t+1} = log(Z_{t+1})$ and ϵ_{t+1}^z is an i.i.d. standard normal shock that is uncorrelated across all firms in the economy and independent of ϵ_{t+1}^x. $\bar{z}$, ρ_z, and σ_z are the mean, autocorrelation, and conditional volatility of firm-specific productivity, respectively.

An important ingredient of this model is the stochastic adjustment cost shock,

$$s_{t+1} = \rho_s s_t + \sigma_s \epsilon_{t+1}^s, \tag{1.11}$$

in which $s_{t+1} = log(S_{t+1})$ and ϵ_{t+1}^s is an i.i.d. standard normal shock that is uncorrelated to all other shocks. ρ_s and σ_s are the persistence and conditional volatility of the adjustment cost process, respectively.

Since the focus is on the production side of the economy, I directly specify the stochastic discount factor without modeling consumer's problem. The pricing kernel is a function of the two aggregate

[20] One can interpret S_t as an extended investment-specific shock similar to Papanikolaou (2011) that affects both capital and labor.

shocks (productivity and adjustment cost shocks) in the economy,

$$M_{t,t+1} = exp(-r_f)\frac{exp(-\gamma_x \Delta x_{t+1} - \gamma_s \Delta s_{t+1})}{E_t[exp(-\gamma_x \Delta x_{t+1} - \gamma_s \Delta s_{t+1})]}, \tag{1.12}$$

where r_f is the log risk-free rate which is constant, $\gamma_x > 0$, and $\gamma_s < 0$ are the loadings of the pricing kernel on the two aggregate shocks. The sign of the loadings (γ_x, γ_s) are from previous studies.[21]

Lastly, the real wage is a function of the aggregate productivity shock,

$$W_t = \tau_1 exp(\tau_2 \Delta x_t), \tag{1.13}$$

where $\tau_1 > 0$ and $0 < \tau_2 < 1$. Here, τ_1 is a scaling factor which represents industry wage premia and τ_2 allows to capture procyclicality of the wage rate reported in Merz and Yashiv (2007).

1.4.3 Firm's Problem

Assuming that a firm's assets are financed only by equity, the firm chooses investments and labor hiring to maximize its dividend equity value. Define a firm's dividend as

$$D_t = Y_t - W_t N_t - Adj_t - F_t, \tag{1.14}$$

where W_t is the wage bill and F_t is fixed operating costs. The firm distributes its dividend from the output net of total investments and hiring costs, as well as fixed costs. Let V_t be the cum-dividend market value of the firm and state variables $(K_t, N_t, x_t, z_t, s_t)$ in period t. In each period, the firm chooses investment (I_t) and hiring (H_t) to maximize its cum-dividend value,

$$V_t = V(K_t, N_t, x_t, z_t, s_t) = \max_{I_t, H_t} E_t\Big[\sum_{j=0}^{\infty} M_{t,t+j} D_{t,t+j}\Big], \tag{1.15}$$

subject to the capital and labor accumulation processes specified in (1.5).

1.4.4 Calibration

Because the model cannot be solved analytically, I solve the firm's optimal investment and hiring problem numerically at a monthly frequency.

In Table 1.11, I report the parameter values used in the simulation. The parameter values chosen in Belo et al. (2014) are set to match various aggregate and firm-level moments of asset prices and real quantities. The original model generates a sizable equity premium (approximately 4.8% per

[21]See, for exmaple, Jermann (1998), Zhang (2005), Kogan and Papanikolaou (2013), and Kogan and Papanikolaou (2014).

annum), a large value premium (approximately 5.5% per annum), and a smooth risk-free rate, and matches key properties of the aggregate wage rate, aggregate profits, and several properties of the firm-level investment and hiring rates in both the time series and the cross-section. The model assumes the same wage process for all firms.

In this study, the source of variation is the persistent wage difference between industries, which proxies for labor adjustment costs. I set benchmark parameter values as in Belo et al. (2014) and generate heterogeneity across industries by assigning different labor cost parameters. Specifically, I calibrate low wage industries by simply setting the wage (τ_1) and labor adjustment costs ($b_n^+, b_n^-, c_n^+, c_n^-$) to be one-third of those of high wage industries. Because the parameters are not exactly calibrated to match real data, this exercise is mostly qualitative.

I simulate a long sample for two wage panels (Low Wage and High Wage) and sort firms into decile portfolios according to their capital investments. Table 1.12 provides the main testable predictions from the previously described model (column (1)). I report the value-weighted investment spread for low and high wage industries. As predicted, the model generates a negative investment spread (high-minus-low portfolio returns), consistent with the theory that optimal investments are high when the expected future marginal profitability of capital is high or when the cost of capital is low.

The key prediction from the simulation is the difference in the magnitude of investment spreads between two industries. I find that investment spreads become larger when labor costs are expensive. In the benchmark calibration (column (1)), the high-minus-low returns for the high wage industry (-0.55%) are larger in terms of magnitude than those of the low wage industry (-0.11%). A similar pattern is found for the hiring spread in column (2). The results are intuitive from the q-theory framework. Given capital-labor complementarity, low wage industries flexibly adjust their capital to changes in the cost of capital in a manner similar to the labor force adjustment.

I also examine alternative calibrations of the model. In column (3), I set a super-persistent wage process by shutting down the wage volatility parameter (τ_2). Less flexible cost induces firm profits to be more volatile, which changes the risk profile of firm. However, I find qualitatively similar high-minus-low spreads. In column (4), I set the same labor adjustment cost parameters (b_n, c_n) for two industries. As a result, the difference in spreads becomes narrower than the benchmark case (-0.44% to -0.07%). This implies that difference in wages alone cannot generate a sizable gap between two investment spreads. As discussed in Belo et al. (2014), the return spread is driven by adjustment costs combined with the aggregate adjustment cost shock, whereas the change in the wage process operates through the operating leverage effect. As such, the results confirm that the operating leverage mechanism does not drive investment-return sensitivity.

Firm investment and hiring react to exogenous aggregate shocks. When the economic environment improves, firms expand capital, and more so for firms whose costs are lower. To investigate the sensitivity of investments to shocks, I draw on impulse responses of capital investment to a 10% positive aggregate productivity shock for both high and low wage industries, as in Figure 1.2.

I compare the impulse response function of high (red line) and low wage (blue line) industries. The responses are measured in percentage point deviations relative to the long-run average values.

I track firm investment for two years after the shock. As shown in Figure 1.2, it is clear that, given the same positive productivity shock, both firms increase their investments. Furthermore, firms in low wage industries increase investments more than firms in high wage industries when positive productivity shocks arrive given low labor costs. This phenomenon supports the results in Table 1.5.

1.4.5 Risk-based Explanation

The steeper investment-return relation for high wage industries can also be linked to broad economic risk. In the framework, productivity and adjustment cost shocks are two aggregate state variables. If the economy experiences a shock that lowers adjustment costs, expanding firms (high capital investment) that face high adjustment costs benefit the most, allowing them to expand faster. As a result, these firms have lower risk and, hence, lower expected returns in equilibrium. This implies that adjustment cost shock carries a negative price of risk. Figure 1.3 illustrates the model's mechanism from the risk perspective. In simulated data (left), the return covariance to an adjustment cost shock shows an increasing pattern across investment portfolios and is more significant for high wage industries, resulting in a steeper investment spread.

Turning to the previous portfolio sort, the results suggest that Fama-French factors (SMB and HML) may not be a proxy for adjustment cost shock because the investment spreads (especially for high wage portfolios) are not fully subsumed by the factors. Therefore, an empirical proxy of adjustment cost shocks is needed to link asset prices to economic fundamentals, although not readily available. In the model, investment portfolios have similar exposure to aggregate productivity shock but have a different exposure to aggregate adjustment cost shocks. This implies that high-minus-low investment portfolios can be used as a proxy for the adjustment cost shock in an economy if the model is a correct specification of the economy. Using this logic, I employ the investment factor (CMA) suggested in Fama and French (2015) and investigate whether the return difference can be attributed to exposure to the adjustment cost shock.

Figure 1.3 (right) shows the CMA factor loadings of portfolios double sorted on wage premia and investment, after controlling for four other Fama-French factors. Similar to the pattern from the simulation, I find that the CMA factor loading spread is larger for high wage industries, consistent with the risk-based explanation of the investment spread in the theoretical framework.[22]

1.4.6 Value Premium

The role of operating inflexibility on asset prices has received significant attention in the recent literature. For example, Carlson et al. (2004) relate operating leverage to the book-to-market effect. Zhang (2005) highlights the effect of costly reversibility and the countercyclical price of risk to value firms, which causes them to be riskier than growth firms, especially in bad times.

[22] Obviously, the estimated alphas are zero for both high and low wage portfolios.

Clearly, the value premium increases with the inflexible adjustment and the operating leverage. In an extended investment-based framework, high wage industries should have larger value premiums than low wage industries because wage affects several dimensions of operational flexibility.[23]

In Table 1.13, I present the average CAPM alphas of two decile value-weighted portfolios sorted on wage premia and book-to-market from either the benchmark simulation (Panel A) or real data (Panel B). From Panel A, I find that high wage firms have higher value premiums than low wage firms. The same patterns are found in the real data. I find that high wage industries tend to have larger value premiums in terms of both magnitude and significance. The value spread, as measured by the CAPM alpha for the low wage portfolio, is 0.44% monthly with significance at the 5% level. Moreover, the monthly high-minus-low alpha for high wage portfolios is 0.66% with significance at the 1% level, which is 50% larger than the low wage portfolio spread. Consistent with the prediction from the model, I find the interaction effect between wage and book-to-market in the cross-section.

1.5 Conclusion

This study identifies theoretical and empirical linkages between stock returns and the labor market through industry wage premia that persist for decades. I exploit industry differences in wage premia as a proxy for labor adjustment costs and find that investments of high wage industries are less elastic to changes in the cost of capital. An extended investment-based model predicts the interaction effect. Labor market friction modeled in this study works in not only labor hiring but also capital investments given the capital-labor complementarity in production.

The inflexibility induced by wages provides useful implications on asset prices and corporate investments. I find that the hiring spread and the value premium are larger in magnitude and significance for high wage firms. Firms paying high wage premia also adjust inputs slower than low wage firms to changes in opportunities. Taken together, my results highlight the importance of labor costs on asset prices and on the dynamics of corporate investments.

[23] Gu et al. (2017) find the wage premia to be positively correlated to their flexibility measure, which proxies for the width of a firm's inaction region.

1.6 Figures and Tables

Figure 1.1 Industry Wage Premia in 1980 and 2010

This figure plots the estimated industry wage premia in 2010 against the premia in 1980. The wage premia is estimated from the regression (1.1). I report the slope coefficient from a simple linear regression that regress industry wage premia in 2010 on the premia estimated in 1980.

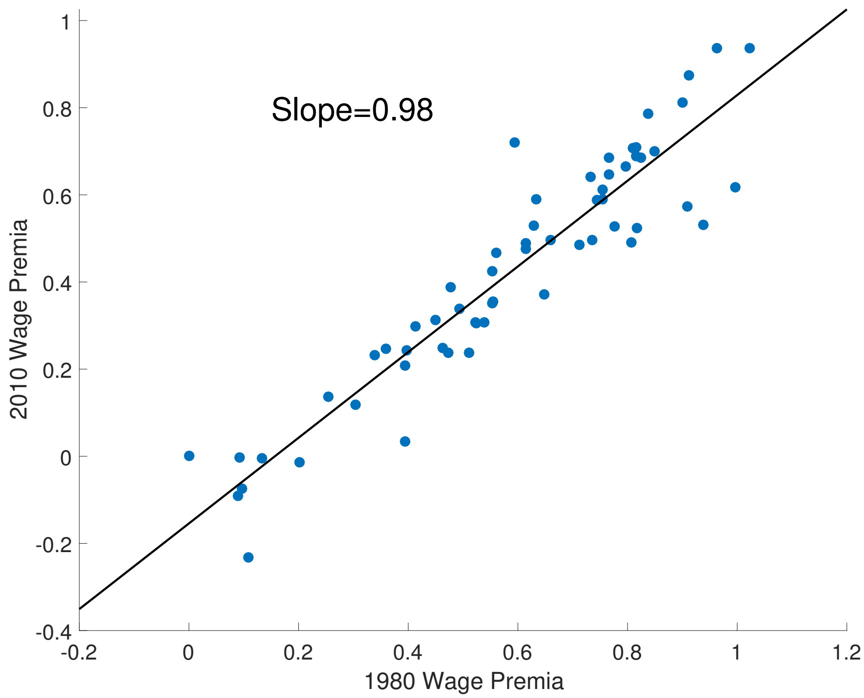


Figure 1.2 Response of Capital Investment to Aggregate Shock

This figure plots the impulse response of firm investment to a 10 percent positive aggregate productivity shock. The response is measured in percentage point deviations relative to the long-run average values.

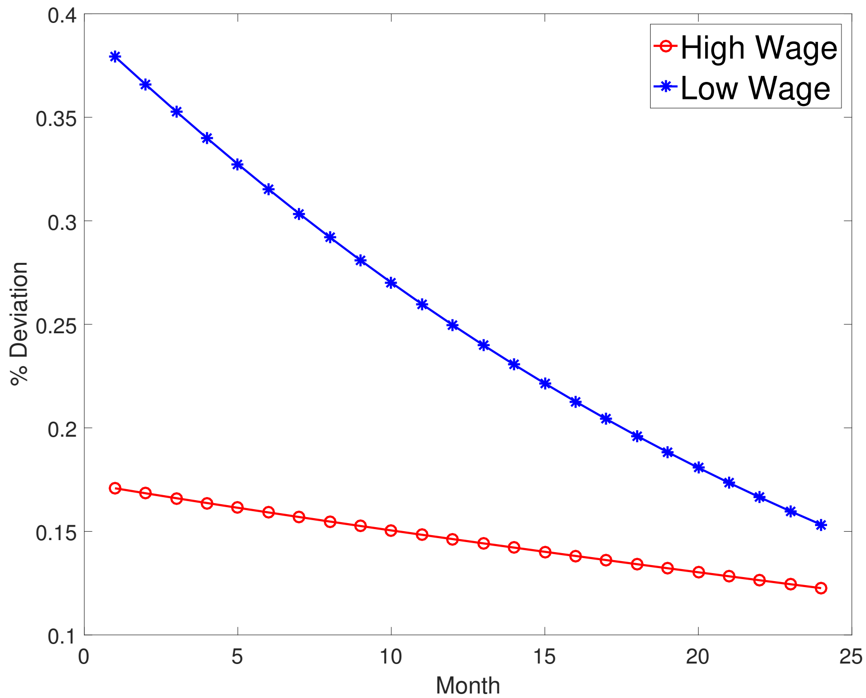
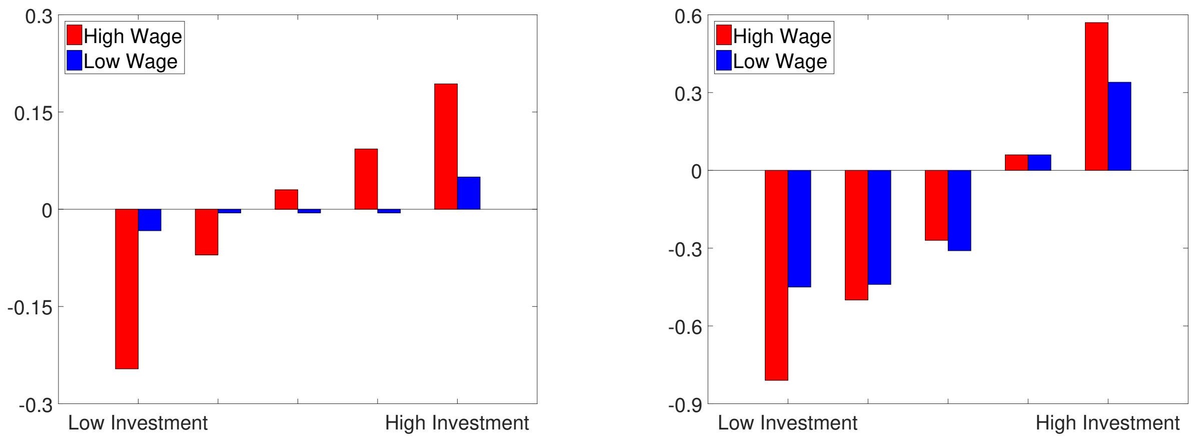


Figure 1.3 Exposures to Adjustment Cost Shock

This figure shows the covariances of investment portfolios to the adjustment cost shock. I compare the simulated data (left) and the real data (right). In each figure, I report low wage (blue) and high wage (red) industries separately. In (a), the covariances are expressed relative to the average across all the portfolios. In (b), I report the portfolio factor loadings on the Fama-French investment factor (CMA), after controlled for other four Fama-French factors.



(a) Simulation

(b) Data

Table 1.1 Industries with High and Low Wage Premia

This table presents the 10 industries with the highest and lowest values of wage premia from the decennial census. Industry wage premia is the estimated from the regression (1.1). Industries are classified into 60 categories described in Appendix B.

Rank	Industry	Wage Premia
	Panel A: Ten Industries with Highest Wage Premia	
1	Coal mining	0.94
2	Railroads	0.94
3	Petroleum and coal products	0.87
4	Metal mining	0.81
5	Oil and gas extraction	0.79
6	Legal services	0.72
7	Water transportation	0.71
8	Security, commodity brokerage, and investment companies	0.71
9	U.S. postal service	0.70
10	Chemicals and allied products	0.69
	Panel B: Ten Industries with Lowest Wage Premia	
51	Education services	0.14
52	Personal services	0.12
53	Food retail	0.03
54	Hotels and lodging places	0.00
55	Miscellaneous services	0.00
56	Eating and drinking	-0.01
57	General merchandiser	-0.01
58	Entertainment and recreation services	-0.07
59	Miscellaneous retail	-0.09
60	Apparel and shoe	-0.23

Table 1.2 Correlation With Other Labor Characteristics

This table presents the time-series average correlation between industry wage premia and labor characteristics. *Wage* is estimated from the regression (1.1). *Unionization* is the percentage of employed workers who are union members. *Skill* is the percentage of skilled workers. Skilled worker is classified at occupational level based on the Specific Vocational Preparation (SVP) score provided by U.S. Department of Labor. Industry skill measure is obtained using the number of workers at the occupational level from the Bureau of Labor Statistics' Occupational Employment Statistics (OES) program. *Mobility* is the labor mobility measure used in Donangelo (2014). *Labor Hiring* is the industry-level gross labor hiring.

Variable	Correlation	Period	Obs
Unionization	0.425	1983-2014	9,758
Skill	0.198	1990-2014	7,400
Labor Mobility	0.237	1990-2011	6,147
Labor Hiring	-0.152	1967-2014	2,415

Table 1.3 Validation Tests

This table presents the association between industry wage premia and labor adjustment costs. The dependent variables are proxies of labor adjustment costs: the amount of time the employer and other staff spent recruiting, screening and interviewing the new hire (*Screening*), the amount of time employees and supervisory staff spent training the new hire (*Training*), and the last new hire productivity gap (*Productivity Gap*) defined as the productivity of the last employee in the position relative to the productivity of the new employee during the second week of employment. *Wage* is the industry wage premia estimated in (1.1). *Size* is the number of employees of the establishment; *Age* is the age of the new hire; *Male* is a dummy variable equals to 1 if the new hire is male; *Skill* is a dummy variable equals to 1 if the newly hired has a high school diploma or more; *Experience* is relevant job experience of the new hire measured in month. The data is extracted from the 1980 Employer Opportunity Pilot Project (EOPP) employer survey. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Screening		*Training*		*Productivity Gap*	
	(1)	(2)	(3)	(4)	(5)	(6)
Wage	2.546***	2.098**	11.518***	8.709***	5.278***	4.877***
	(2.77)	(2.15)	(3.65)	(2.63)	(3.36)	(2.94)
Size		0.005***		0.012**		0.004
		(3.70)		(2.57)		(1.63)
Age		-0.025		0.057		-0.037
		(-0.84)		(0.57)		(-0.72)
Male		-1.581***		-1.841		-3.505***
		(-3.46)		(-1.18)		(-4.51)
Skill		2.431***		7.189***		4.394***
		(4.17)		(3.63)		(4.44)
Experience		0.011**		-0.058***		-0.005
		(2.27)		(-3.58)		(-0.63)
Const	6.330***	5.201***	30.423***	27.176***	14.220***	13.594***
	(13.94)	(5.31)	(19.55)	(8.16)	(18.33)	(8.16)
R^2	0.31%	2.68%	0.56%	2.29%	0.46%	2.72%
Obs	2,460	2,337	2,374	2,273	2,449	2,332

Table 1.4 Summary Statistics

This table reports time-series averages of median portfolio characteristics of the 20 portfolios sorted on the industry wage premia and investment-to-assets ratio ($IA1$). Based on information available at the end of the previous years, in June of each year, I sort stocks into two groups using estimated wage premia. Meanwhile, independently, firms are grouped into decile portfolios based on the NYSE breakpoints of investment variable. $Wage$ is the estimated industry wage premia; $IA1$ is the investment-to-assets ratio; $IA2$ is the asset growth; $IA3$ is the capital expenditures divided by property, plant and equipment; $Hire$ is the change in number of employees divided by lagged number of employees; $Size$ is the log market value of equity; BM is the book-to-market ratio; $Mkt.Lev$ is the total book debt divided by the sum of market value of equity and total book debt; ROA is the return on assets. The sample period is from 1967 through 2014.

		IA				
	All Firms	L	2	5	9	H
	Panel A: Low Wage Portfolio Characteristics					
$Wage$	0.485	0.502	0.497	0.486	0.471	0.452
$IA1$	0.070	-0.085	-0.007	0.055	0.187	0.377
$IA2$	0.098	-0.074	-0.008	0.067	0.215	0.582
$IA3$	0.259	0.127	0.158	0.237	0.369	0.612
$Hire$	0.045	-0.085	-0.026	0.030	0.128	0.296
$Size$	4.417	3.582	4.055	4.692	4.685	4.431
BM	0.708	0.979	0.918	0.740	0.583	0.506
$Mkt.\ Lev$	0.194	0.293	0.238	0.187	0.176	0.182
ROA	0.151	0.074	0.106	0.150	0.196	0.221
	Panel B: High Wage Portfolio Characteristics					
$Wage$	0.746	0.746	0.744	0.750	0.751	0.772
$IA1$	0.071	-0.085	-0.007	0.056	0.186	0.387
$IA2$	0.089	-0.076	-0.013	0.058	0.212	0.565
$IA3$	0.233	0.127	0.141	0.200	0.363	0.590
$Hire$	0.036	-0.098	-0.031	0.022	0.118	0.300
$Size$	4.652	3.814	4.186	5.069	4.752	4.600
BM	0.669	0.842	0.836	0.700	0.576	0.502
$Mkt.\ Lev$	0.175	0.238	0.197	0.178	0.162	0.178
ROA	0.139	0.066	0.094	0.138	0.182	0.211

Table 1.5 Aggregate Shocks and Corporate Investment

This table shows the response of firm capital investments to aggregate shocks. The dependent variables are proxies of firm capital investments and labor hiring, where $IA1$ is the investment-to-assets ratio, $IA2$ is the asset growth, $IA3$ is the capital expenditures divided by property, plant and equipment, and $Hire$ is the labor hiring. The real GDP growth rate is employed as a proxy for the time-varying aggregate productivity shock ($Shock$). $Wage$ is the industry wage premia. $Tobin's\ q$ is the market-to-book ratio; $Cash\ Flow$ is the earnings before extraordinary items plus depreciation divided by capital stock; $Cash$ is the ratio of cash and cash equivalent to assets; $Mkt.Lev$ is the total book debt divided by the sum of market value of equity and total book debt. The sample period is from 1967 through 2014. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. The numbers in parentheses are t-statistics clustered at the firm-level.

	$IA1$		$IA2$		$IA3$		$Hire$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Shock$	0.005***	0.010***	0.009***	0.021***	0.004***	0.017***	0.014***	0.017***
	(18.41)	(14.75)	(16.35)	(13.61)	(6.88)	(12.35)	(30.72)	(14.29)
$Shock * Wage$		-0.010***		-0.020***		-0.023***		-0.006***
		(-9.53)		(-9.95)		(-11.98)		(-3.85)
$Wage$		0.213***		0.275***		0.299***		0.177***
		(31.36)		(21.10)		(22.76)		(17.44)
$Tobin's\ q$	0.025***	0.025***	0.117***	0.116***	0.061***	0.060***	0.035***	0.035***
	(23.58)	(23.55)	(27.45)	(27.36)	(19.60)	(19.47)	(18.42)	(18.39)
$Cash\ Flow$	0.003***	0.003***	0.006***	0.005***	0.010***	0.010***	0.005***	0.005***
	(9.52)	(9.12)	(4.00)	(3.82)	(6.33)	(6.17)	(5.71)	(5.57)
$Cash$	0.031***	0.029***	-0.052***	-0.055***	0.316***	0.313***	0.152***	0.150***
	(12.17)	(11.42)	(-5.19)	(-5.49)	(28.38)	(28.17)	(23.24)	(23.02)
$Mkt.\ Lev$	-0.022***	-0.022***	-0.028***	-0.028***	-0.039***	-0.039***	-0.021***	-0.021***
	(-25.96)	(-27.65)	(-12.09)	(-12.50)	(-17.56)	(-18.13)	(-14.31)	(-14.74)
$Firm\ FE$	Y	Y	Y	Y	Y	Y	Y	Y
R^2	29.08%	30.38%	27.75%	28.10%	41.77%	42.22%	26.40%	26.72%
$Total\ Obs$	101,436	101,436	102,427	102,427	101,416	101,416	99,083	99,083

Table 1.6 Aggregate Shocks and Industry Investment

This table shows the response of industry capital investments to aggregate shocks. The dependent variables are proxies of capital investments and labor hiring, where $IA1$ is the investment-to-assets ratio, $IA2$ is the asset growth, $IA3$ is the capital expenditures divided by property, plant and equipment, and $Hire$ is the labor hiring. The real GDP growth rate is employed as a proxy for the time-varying aggregate productivity shock ($Shock$). $Wage$ is the industry wage premia. $Tobin's\ q$ is the market-to-book ratio; $Cash\ Flow$ is the earnings before extraordinary items plus depreciation divided by capital stock; $Cash$ is the ratio of cash and cash equivalent to assets; $Mkt.Lev$ is the total book debt divided by the sum of market value of equity and total book debt. All variables are aggregated at the industry-level. The sample period is from 1967 through 2014. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. The numbers in parentheses are t-statistics clustered at the industry-level.

	$IA1$		$IA2$		$IA3$		$Hire$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Shock$	0.008***	0.014***	0.013***	0.025***	0.007***	0.016***	0.013***	0.016***
	(6.80)	(8.80)	(8.11)	(7.79)	(5.06)	(8.28)	(8.78)	(4.91)
$Shock * Wage$		-0.016***		-0.025***		-0.020***		-0.007
		(-7.01)		(-5.45)		(-7.21)		(-1.59)
$Wage$		0.204***		0.214***		0.211***		0.101***
		(13.11)		(8.65)		(7.63)		(4.51)
$Tobin's\ q$	-0.009	0.012	0.003	0.022	-0.001	0.019	0.036*	0.047**
	(-0.94)	(1.42)	(0.23)	(1.40)	(-0.08)	(1.41)	(1.90)	(2.38)
$Cash\ Flow$	0.026	0.021	0.065	0.058	0.088**	0.082**	0.024	0.022
	(1.53)	(1.23)	(1.60)	(1.40)	(2.53)	(2.56)	(0.69)	(0.65)
$Cash$	0.079	0.032	0.189**	0.145	0.296***	0.250***	0.306***	0.282**
	(1.41)	(0.72)	(2.03)	(1.59)	(3.21)	(3.07)	(2.90)	(2.61)
$Mkt.\ Lev$	-0.009	-0.012	-0.011	-0.014	0.001	-0.002	0.018	0.017
	(-0.63)	(-0.93)	(-0.56)	(-0.73)	(0.06)	(-0.13)	(0.92)	(0.86)
$Ind\ FE$	Y	Y	Y	Y	Y	Y	Y	Y
R^2	17.88%	27.36%	17.83%	21.41%	40.18%	45.30%	19.30%	20.09%
$Total\ Obs$	2,305	2,305	2,305	2,305	2,304	2,304	2,299	2,299

Table 1.7 One-way Sorts on Capital Investment

This table provides average monthly returns and alphas for decile portfolios sorted on investment variables. The sorting variables are investment-to-assets ($IA1$), asset growth ($IA2$), and capital expenditures divided by property, plant and equipment ($IA3$). Based on information available at the end of the previous years, I form equal-weighted (Panel A) and value-weighted (Panel B) decile portfolios in June of each year. Alphas are estimated from the Fama-French three factor model. The sample period is from 1967 through 2014. *, **, and *** for the High-Low portfolio alphas denote statistical significance at the 10%, 5%, and 1% levels, respectively. The numbers in parentheses are t-statistics based on White (1980) robust standard errors.

	Low	High	High-Low	Low	High	High-Low	Low	High	High-Low
			Panel A : Equal-Weighted Returns						
	$IA1$			$IA2$			$IA3$		
Excess Returns	1.10	0.11	-0.99***	1.15	0.14	-1.01***	1.02	0.40	-0.63***
	(3.67)	(0.34)	(-8.38)	(3.49)	(0.42)	(-8.20)	(3.67)	(1.20)	(-5.02)
Fama-French α	0.22	-0.71	-0.94***	0.28	-0.60	-0.88***	0.18	-0.33	-0.50***
	(1.96)	(-5.24)	(-8.26)	(1.93)	(-4.71)	(-7.98)	(1.63)	(-2.77)	(-5.60)
			Panel B : Value-Weighted Returns						
	$IA1$			$IA2$			$IA3$		
Excess Returns	0.84	0.23	-0.61***	0.76	0.26	-0.50***	0.72	0.34	-0.38*
	(3.56)	(0.87)	(-4.31)	(3.11)	(0.93)	(-3.14)	(3.08)	(1.11)	(-1.88)
Fama-French α	0.15	-0.29	-0.44***	0.04	-0.18	-0.22*	0.01	-0.04	-0.06
	(1.69)	(-2.84)	(-3.32)	(0.41)	(-2.20)	(-1.67)	(0.13)	(-0.38)	(-0.35)

Table 1.8 Two-way Sorts on Wage and Capital Investment

This table provides average monthly returns and alphas for low, high, and high-minus-low portfolios double sorted on industry wage premia and investment variables. The sorting variables are investment-to-assets ($IA1$), asset growth ($IA2$), and capital expenditures divided by property, plant and equipment ($IA3$). Based on information available at the end of the previous years, I sort stocks into two groups using estimated wage premia. Meanwhile, independently, firms are grouped into decile portfolios based on the NYSE breakpoints of investment variable. I form equal-weighted (Panel A) and value-weighted (Panel B) portfolios in June of each year. Alphas are estimated from the Fama-French three factor model. The sample period is from 1967 through 2014. *, **, and *** for the High-Low portfolio alphas denote statistical significance at the 10%, 5%, and 1% levels, respectively. The numbers in parentheses are t-statistics based on White (1980) robust standard errors.

		Low	High	High-Low	Low	High	High-Low	Low	High	High-Low
		Panel A : Equal-Weighted Returns								
		$IA1$			$IA2$			$IA3$		
Excess Returns	Low Wage	0.99	0.18	-0.81***	1.02	0.18	-0.84***	0.95	0.48	-0.47***
		(3.40)	(0.57)	(-6.55)	(3.19)	(0.54)	(-6.36)	(3.49)	(1.50)	(-3.41)
	High Wage	1.22	0.12	-1.11***	1.26	0.16	-1.10***	1.09	0.33	-0.76***
		(3.81)	(0.35)	(-7.68)	(3.62)	(0.48)	(-8.19)	(3.68)	(0.95)	(-5.40)
	Difference			-0.30**			-0.26**			-0.29**
				(-2.13)			(-2.23)			(-2.33)
Fama-French α	Low Wage	0.10	-0.63	-0.73***	0.13	-0.57	-0.70***	0.08	-0.25	-0.33***
		(0.90)	(-4.42)	(-6.39)	(0.96)	(-4.06)	(-6.05)	(0.70)	(-2.05)	(-3.32)
	High Wage	0.34	-0.72	-1.06***	0.39	-0.57	-0.97***	0.26	-0.39	-0.65***
		(2.47)	(-4.64)	(-7.46)	(2.35)	(-4.29)	(-7.78)	(2.02)	(-2.83)	(-5.72)
	Difference			-0.33**			-0.27**			-0.32***
				(-2.35)			(-2.29)			(-2.64)
		Panel B : Value-Weighted Returns								
		$IA1$			$IA2$			$IA3$		
Excess Returns	Low Wage	0.89	0.37	-0.52***	0.83	0.43	-0.40*	0.75	0.51	-0.24
		(3.48)	(1.28)	(-2.91)	(3.14)	(1.41)	(-1.88)	(3.06)	(1.64)	(-1.07)
	High Wage	0.81	0.14	-0.67***	0.72	0.16	-0.57***	0.67	0.17	-0.50**
		(3.33)	(0.51)	(-3.89)	(2.85)	(0.55)	(-3.23)	(2.76)	(0.53)	(-2.13)
	Difference			-0.15			-0.17			-0.26
				(-0.65)			(-0.74)			(-1.16)
Fama-French α	Low Wage	0.11	-0.19	-0.29*	0.07	0.02	-0.06	-0.04	0.10	0.14
		(0.92)	(-1.39)	(-1.80)	(0.54)	(0.14)	(-0.31)	(-0.34)	(0.81)	(0.81)
	High Wage	0.16	-0.38	-0.54***	0.02	-0.31	-0.33**	-0.01	-0.21	-0.19
		(1.36)	(-2.85)	(-3.13)	(0.17)	(-2.66)	(-2.02)	(-0.10)	(-1.36)	(-0.96)
	Difference			-0.24			-0.27			-0.33
				(-1.04)			(-1.17)			(-1.42)

Table 1.9 Fama-MacBeth Regressions

This table provides the second stage Fama-MacBeth regressions of monthly excess stock returns on the investment (IA), wage premia ($Wage$), and the interaction term between investment and wage premia ($IA * Wage$) along with a set of controls. I use investment-to-assets ($IA1$) to proxy for firm investment from column (1) to (3), asset growth ($IA2$) from column (4) to (6), and capital expenditures divided by property, plant and equipment ($IA3$) from column (7) to (9). $Wage$ is the wage premia estimated in equation (1.1). $Size$ is log market capitalization; $log(BM)$ is the log book-to-market ratio; $R^E_{2,12}$ is the past 12 month stock return skipping the most recent month; R^E_1 is the past 1 month stock return; $Hire$ is the change in number of employees divided by lagged number of employees; $Idiosyn$ is the idiosyncratic risk computed as the logistic transformation of the coefficient of determination from a regression of daily excess returns on the Fama-French three factor model; $Mkt.\ Lev$ is the total book debt divided by the sum of market value of equity and total book debt; $Cash\ Flow$ is the earnings before extraordinary items plus depreciation divided by capital stock. The sample period is from 1967 through 2014. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. *Avg Obs* is the average firm-month observation in the sample. The numbers in parentheses are t-statistics based on the White (1980) standard errors.

	$IA1$			$IA2$			$IA3$		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
IA	-0.994***	-0.555**	-0.331	-0.465***	-0.301***	-0.308***	-0.266***	-0.139	-0.064
	(-4.11)	(-2.56)	(-1.53)	(-4.20)	(-3.12)	(-2.91)	(-2.64)	(-1.54)	(-0.62)
$IA * Wage$	-0.876**	-1.114***	-1.090***	-0.291*	-0.352**	-0.388**	-0.382**	-0.398**	-0.429**
	(-2.21)	(-2.96)	(-2.84)	(-1.77)	(-2.21)	(-2.21)	(-2.31)	(-2.57)	(-2.49)
$Wage$	0.092	0.195	0.182	0.03	0.127	0.117	0.072	0.181	0.17
	(0.69)	(1.55)	(1.49)	(0.22)	(0.98)	(0.92)	(0.53)	(1.39)	(1.33)
$Size$		-0.07	-0.098**		-0.073*	-0.099**		-0.080*	-0.105**
		(-1.60)	(-2.38)		(-1.67)	(-2.38)		(-1.87)	(-2.56)
$log(B/M)$		0.316***	0.316***		0.303***	0.317***		0.311***	0.320***
		(5.03)	(5.82)		(5.00)	(5.87)		(5.20)	(5.93)
$R^E_{2,12}$		0.005***	0.005***		0.005***	0.005***		0.005***	0.005***
		(3.02)	(3.27)		(3.08)	(3.28)		(3.15)	(3.31)
R^E_1		-0.060***	-0.059***		-0.060***	-0.059***		-0.060***	-0.059***
		(-15.00)	(-14.90)		(-15.10)	(-14.88)		(-14.98)	(-14.84)
$Hire$			-0.215***			-0.177**			-0.390***
			(-2.85)			(-2.43)			(-5.66)
$Idiosyn$			-0.175***			-0.176***			-0.176***
			(-5.11)			(-5.13)			(-5.14)
$Mkt.\ Lev$			-0.038*			-0.047**			-0.052**
			(-1.73)			(-2.20)			(-2.46)
$Cash\ Flow$			-0.004			-0.001			-0.008
			(-0.21)			(-0.04)			(-0.38)
Avg R^2	0.80%	4.45%	5.51%	0.89%	4.47%	5.49%	0.93%	4.46%	5.51%
Avg Obs	2,781	2,744	2,247	2,812	2,775	2,268	2,769	2,733	2,247

Table 1.10 Portfolio Sorts on Labor Hiring

This table provides average monthly returns and alphas for low, high, and high-minus-low portfolios sorted on industry wage premia and labor hiring. The sorting variables is the change in number of employees divided by lagged number of employees ($Hire$). Based on information available at the end of the previous years, I sort stocks into one-way decile hiring portfolios based on the NYSE breakpoints of labor hiring variable (Panel A) and two-way wage-hiring portfolios similar to Table 1.8 (Panel B) in June of each year. I report equal-weighted and value-weighted portfolio results. Alphas are estimated from the Fama-French three factor model. The sample period is from 1967 through 2014. *, **, and *** for the High-Low portfolio alphas denote statistical significance at the 10%, 5%, and 1% levels, respectively. The numbers in parentheses are t-statistics based on White (1980) robust standard errors.

		$Hire$			$Hire$		
		Low	High	High-Low	Low	High	High-Low
Panel A : One-way Sort on Hiring							
		Equal-Weighted Returns			Value-Weighted Returns		
Excess Returns		1.02	0.29	-0.72***	0.66	0.37	-0.28*
		(3.30)	(0.91)	(-6.82)	(2.84)	(1.36)	(-1.81)
Fama-French α		0.14	-0.46	-0.60***	0.00	-0.04	-0.05
		(1.12)	(-3.81)	(-6.28)	(0.04)	(-0.51)	(-0.38)
Panel B : Two-way Sort on Wage and Hiring							
		Equal-Weighted Returns			Value-Weighted Returns		
Excess Returns	Low Wage	0.87	0.38	-0.49***	0.67	0.56	-0.11
		(2.87)	(1.18)	(-4.27)	(2.76)	(1.88)	(-0.54)
	High Wage	1.13	0.25	-0.88***	0.64	0.24	-0.39**
		(3.49)	(0.76)	(-7.19)	(2.62)	(0.87)	(-2.18)
	Difference			-0.39***			-0.28
				(-3.45)			(-1.34)
Fama-French α	Low Wage	0.00	-0.37	-0.37***	-0.04	0.13	0.17
		(0.01)	(-2.86)	(-3.63)	(-0.38)	(1.09)	(1.03)
	High Wage	0.25	-0.50	-0.75***	0.01	-0.18	-0.19
		(1.80)	(-3.85)	(-6.61)	(0.06)	(-1.59)	(-1.22)
	Difference			-0.38***			-0.36*
				(-3.33)			(-1.71)

Table 1.11 Parameter Values for Calibration

This table presents the parameter values used in the simulation. The first number in parentheses is used to solve low wage industries, and the second number is used to solve high wage industries.

Parameter	Symbol	Value
Weight of physical capital in the production function	α	0.36
Return to scale	θ	0.85
Elasticity of substitution between capital and labor	ϕ	0.5
Rate of depreciation for capital	δ_k	0.01
Quit rate of labor	δ_n	0.01
Fixed operating cost	f	0.0105
Convex parameters in capital adjustment cost	c_k^+/c_k^-	3.10/34.10
Convex parameters in labor adjustment cost	c_n^+/c_n^-	[0.4 1.2]/[0.4 1.2]
Non-convex parameters in capital adjustment cost	b_k^+/b_k^-	0 .04/0.08
Non-convex parameters in labor adjustment cost	b_n^+/b_n^-	[0.05 0.16]/[0.07 0.20]
Multiplicative coefficient on wage rate process	τ_1	[0.0032 0.0095]
Sensitivity of the wage rate to aggregate productivity	τ_2	0.90
Average growth rate of aggregate productivity	μ_x	0.13/12
Conditional volatility of aggregate productivity	σ_x	0.055
Average level of firm-specific productivity	$\bar{z}$	-3.4
Persistence coefficient of firm-specific productivity	ρ_z	0.97
Conditional volatility of firm-specific productivity	σ_z	0.1
Persistence coefficient of adjustment cost wedge	ρ_s	0.97
Conditional volatility of adjustment cost wedge	σ_s	0.35
Real risk-free rate	r_f	1.65/12
Loading of the stochastic discount factor on aggregate productivity shock	γ_x	6.75
Loading of the stochastic discount factor on the adjustment cost shock	γ_s	-14.5

Table 1.12 Two-way Sorts on Wage and Capital Investment In Simulated Data

This table provides asset pricing moments from the simulated data, obtained as averages from 500 simulations. The numbers reported are monthly value-weighted high-minus-low returns for decile portfolios sorted on capital investment (IA) or labor hiring ($Hire$). I report the spread of low and high wage industries. *Benchmark* is the benchmark simulation based on Table 1.11. *Persistent Wage* is the simulation, shutting down the wage volatility parameter (τ_2). *Same Adj* is the simulation, using the same labor adjustment cost parameters (b_n, c_n) both for low and high wage industries.

	(1)	(2)	(3)	(4)
	Benchmark		*Persistent Wage*	*Same Adj*
	IA	$Hire$		
Low Wage	-0.11	-0.14	-0.12	-0.48
	(-3.42)	(-4.39)	(-3.53)	(-10.04)
High Wage	-0.55	-0.56	-0.56	-0.55
	(-9.09)	(-9.13)	(-9.13)	(-9.10)

Table 1.13 Two-way Sorts on Wage and Book-to-market

This table provides average monthly value-weighted alphas for low, high, and high-minus-low portfolios double sorted on industry wage premia and book-to-market (BM). Similar to Table 1.8. I form 20 portfolios sorted on wage and book-to-market using the simulated data (Panel A) and the real data (Panel B). Alphas are estimated from the CAPM model. The sample period is from 1967 through 2014 for Panel B. *, **, and *** for the High-Low portfolio alphas denote statistical significance at the 10%, 5%, and 1% levels, respectively. The numbers in parentheses are t-statistics based on White (1980) robust standard errors.

		BM					
		Low	2	5	9	High	High-Low
Panel A : Two-way Sorts on Wage and Book-to-Market in Simulated Data							
$CAPM\ \alpha$	Low Wage	-0.19	-0.14	-0.03	0.13	0.23	0.42***
		(-6.48)	(-5.10)	(-1.39)	(5.21)	(8.62)	(9.33)
	High Wage	-0.27	-0.18	-0.05	0.20	0.33	0.59***
		(-7.03)	(-5.19)	(-1.42)	(5.99)	(9.42)	(10.10)
Panel B : Two-way Sorts on Wage and Book-to-Market in Real Data							
$CAPM\ \alpha$	Low Wage	-0.10	-0.08	0.22	0.43	0.34	0.44**
		(-0.93)	(-0.85)	(1.87)	(2.86)	(2.05)	(2.04)
	High Wage	-0.23	-0.03	0.15	0.50	0.43	0.66***
		(-2.18)	(-0.31)	(1.39)	(3.64)	(2.78)	(3.05)
	Difference						0.22
							(1.09)

CHAPTER 2

ANOMALIES IN THE JOINT CROSS SECTION OF EQUITY AND CORPORATE BOND RETURNS

2.1 Introduction

Rational pricing guarantees that securities will be priced consistently across markets. This implies that pricing phenomena in cross-sectional equity returns, or so-called anomalies, must also appear in corporate bond returns. Rational pricing, however, imposes even stronger restrictions. Since equity and corporate bonds are contingent claims on the same underlying firms, the relative magnitudes of cross-sectional return premia in equity and corporate bonds should also be consistent with each other. Although there is an abundance of research debating whether rational or behavioral theories explain the cross section of returns, this simple but powerful insight has not received much attention.[1]

In the corporate bond pricing literature, typical workhorse models based on the contingent claims framework are the so-called structural credit risk models à la Merton (1973). In these models, equity and corporate bonds are linked through no-arbitrage pricing, which imposes restrictions on the joint cross section of expected equity and corporate bond returns. In other words, rational pricing governs *how* equity and corporate bonds should be jointly priced in the cross section, independently of *what* characteristics drive cross-sectional expected returns. These restrictions are not tested in the empirical equity pricing or corporate bond literatures.

The purpose of this paper is to attempt to bridge the gap between these two literatures by examining the joint cross section of equity and corporate bond returns. Using an extensive panel dataset of corporate bond returns, we document which variables that are known to price the cross section of equity returns also price the cross section of corporate bond returns, since the literature focuses largely on equity returns. Among numerous so-called anomaly variables, we examine mainly asset growth, investment, gross profitability, and net issuance, since many rational theories for these anomalies work through the underlying firm channels (e.g., the q-theory or the real option theory) and thus should apply to both equity and corporate bonds of the same firm.[2] In addition to these anomalies, we investigate more traditional and prominent anomaly variables such as book-to-market and momentum as well as idiosyncratic volatility, equity beta, and accruals.

[1] See, for example, Carlson et al. (2004) and Anderson and Garcia-Feijóo (2006) for rational explanations; see also, among many other studies, Baker and Wurgler (2006), and Stambaugh et al. (2012) for behavioral explanations of cross-sectional equity returns. Also see Harvey et al. (2016) for a summary of the literature.

[2] See, e.g., Lyandres et al. (2008), Xing (2008), and Li et al. (2009).

From the viewpoint of contingent claim pricing, it is not a straightforward question whether the same set of anomaly variables should explain both equity and corporate bonds in the cross section. On the one hand, even when the underlying economic channel for anomalies operates only through equity, the same anomalies could appear in corporate bonds of the same firms. Suppose a firm's market value of equity increases due to a behavioral reason independently of a change in the firm's fundamentals. The increase is also likely to increase the underlying firm value, which in turn should lead to a higher bond price, since the bond is also a contingent claim on the firm. Thus, even for anomalies that are driven by investor irrationality only in the equity market, one might expect to observe similar cross-sectional return patterns in the corresponding corporate bonds through this underlying firm value channel.

On the other hand, there is also a reason that anomaly variables do not necessarily explain corporate bond returns, because equity and bond returns are not monotonically related in the cross section. As an example, consider the gross profitability anomaly, in which high profitability firms earn higher equity returns than those of low profitability firms. If high profitability firms have low default risk and their bonds are very safe compared with low profitability firms, then we should not expect to observe the gross profitability anomaly in corporate bond returns. In the framework of contingent claim pricing, corporate bond returns are approximately the product of equity returns and the sensitivity, or hedge ratio, of debt to equity. Corporate bonds with little default risk have very low hedge ratios and their returns are not particularly sensitive to the equity returns of the same firms. The anomalies at the equity level will not necessarily appear in the corporate bond returns of such firms. Thus, cross-sectional returns on corporate bonds in the dimensions along the anomaly variables should be interpreted in conjunction with their sensitivity to the equity of the same firms.

Despite the importance of the corporate bond market for both investors and corporate borrowers, we have seen relatively fewer studies of the cross section of bond returns compared with equity returns.[3] The most likely reason is that corporate bond price data are not readily available, since bonds are traded over the counter. Employing the Reuters Fixed Income Database (commonly known as the EJV) and also the Lehman Brothers database, which together span over 3 million bond-month observations across 3,498 firms and 75% of the CRSP/Compustat universe in terms of market capitalization from 1979 through 2012, we provide a thorough investigation of cross-sectional corporate bond returns.

We make the following contributions to the literature. First, we document which variables known to price the cross section of equity returns also price cross-sectional bond returns on the same issuing firms. We find that asset growth and investment are negative related to future corporate bond returns, as they are to equity returns. In equal-weighted decile portfolios sorted on asset growth, for example, the high-minus-low portfolio return is -0.32% monthly, which is economically

[3]Several studies investigate cross-sectional returns in credit markets. See, for example, Gebhardt et al. (2005a), Gebhardt et al. (2005b), Lok and Richardson (2011), Jostova et al. (2013), Lin et al. (2013), Chordia et al. (2016), and Bai et al. (2016). For studies of rating-sorted bond portfolio returns, see Fama and French (1993) and Koijen et al. (2017) , among many others.

significant (over 30% of that on the corresponding equity portfolio returns). The high-minus-low return on portfolios sorted on investment is -0.24% monthly, which is approximately 30% of the corresponding equity returns. In contrast, we find that other anomaly variables are not consistently priced in corporate bond returns. In particular, idiosyncratic volatility tends to be positively related to future returns on equal-weighted bond portfolios, unlike with equity returns. Gross profitability is weakly and negatively related to bond returns among small bond issues, whereas it is positively related to equity returns. We find no evidence that net issuance, beta, or accrual are reliably related to corporate bond returns. These results are fairly robust. We obtain consistent results at the portfolio or individual firm levels or when we eliminate illiquid bonds using the liquidity constraint filter of the Barclays Aggregate Corporate Bond Index.

Next, we investigate these apparent disparities in cross-sectional returns on equity and corporate bond returns to determine whether they can be reconciled with their hedge ratios. Interestingly, among those anomalies in which we find inconsistent cross-sectional return patterns (i.e., net issuance, gross profitability, idiosyncratic volatility, beta, and accrual), the hedge ratios are actually consistent with the joint cross section of equity and bond returns. The main reason for this is that hedge ratios are tend to be fairly small. In value-weighted bond portfolios sorted on net issuance, for example, the hedge ratios are estimated to be 0.03 or smaller. Thus, the net issuance effect on corporate bonds that is consistent with their exposure to underlying firms should be close to zero. We find similar results for gross profitability, idiosyncratic volatility, beta, and accrual. These results are fairly robust. The conclusion remains the same when we employ the hedge ratios derived from structural credit risk models, following Schaefer and Strebulaev (2008).[4]

On the other hand, among the anomalies in which the equity-level anomaly variables also explain corporate bond returns, we find that the cross-sectional bond return premia tend to be too large compared with their hedge ratios. For portfolios sorted on asset growth and momentum, e.g., high-minus-low corporate bond returns are greater by around 2% per year than can be explained by hedge ratios. The differences in return premia are not subsumed by the standard risk factors such as the Carhart (1997) four factors, the Fama and French (2015) investment factors, the two bond market factors of Fama and French (1993), or the equity and bond liquidity factors of Pastor and Stambaugh (2003) and Lin et al. (2011). These results suggest that the asset growth and momentum effects at the corporate bond level are not driven only by changes in underlying firm values. Our findings also complement those in Jostova et al. (2013), who show that corporate bond momentum is not merely a manifestation of equity momentum.

Having documented the extent to which the cross-sectional bond return premia are consistent with their hedge ratios and equity return premia, we turn to behavioral forces as a potential driver of cross-sectional bond returns. Our analysis is largely motivated by Stambaugh et al. (2012), who show that long-short equity strategies exploiting anomalies are particularly profitable on the short side when aggregate investor sentiment is high, which suggests that overpricing combined

[4]Our hedge ratio estimates are largely consistent with those in Schaefer and Strebulaev (2008), who report hedge ratio estimates of approximately 0.04 for BBB-rated bonds.

with short-sale impediments partly drives anomalies. To isolate the sentiment effect on corporate bonds from its effect on equity, we regress returns on corporate bonds that are hedged against the equity risk of the same firms on the aggregate investor sentiment measure of Baker and Wurgler (2006). Consistent with Stambaugh et al. (2012), we find that hedged returns on long-short anomaly portfolios increase with lagged investor sentiment, among other variables. In a predictive regression setting, the expected returns on the long-short portfolios become greater with sentiment, especially on the short side of the portfolios. The results remain robust even after controlling for instruments for the time-varying market risk premium and the VIX. These results suggest that behavioral forces are also at work in driving cross-sectional corporate bond returns.

Our paper contributes to the growing body of literature on the cross section of corporate bond returns. In earlier studies, Gebhardt et al. (2005a) show that default and term betas and yield-to-maturity among other bond characteristics can explain the cross section of corporate bond returns. Gebhardt et al. (2005b) examine momentum spillover from equity to bonds. Our paper differs from their studies by examining the cross section of bond returns in the dimension of the nine anomaly variables in the equity literature, using a broader and longer sample of corporate bonds. Jostova et al. (2013) show significant momentum in corporate bonds even after controlling for equity momentum and systematic risk. Our results complement theirs by documenting substantial asset growth and investment effects in corporate bonds. In addition, Bai et al. (2016) show that bond-level distributional characteristics such as volatility and skewness explain future bond returns. In contrast, we examine equity- or firm-level characteristics in explaining bond returns.

In a closely related contemporaneous working paper, Chordia et al. (2016) also study which anomaly variables predict corporate bond returns. The important difference distinguishing our paper is that we examine the cross market relationship using hedge ratios, while their paper focuses mainly on documenting anomalies in bond returns. While most of their results are consistent with ours, one seemingly different result of theirs is that profitability is negatively priced in bond returns. The difference occurs mainly because they employ profitability instead of the gross profitability of Novy-Marx (2013), which we employ in our paper.[5] In addition, our main results are based on large, relatively more liquid bond issues, since we use firm-level returns by value-weighting individual bond returns within the same firms and also eliminate matrix pricing, which does not reflect market prices.[6]

Our paper also adds to the literature on credit-equity market integration. Schaefer and Strebulaev (2008) show that structural credit risk models provide fairly accurate estimates of hedge ratios of individual bonds. We build on their results by examining the extent to which the expected returns implied from these hedge ratios are consistent with observed expected returns on corporate

[5] In fact, footnote 10 in Chordia et al. (2016) states that their results on profitability is weaker when they use gross profitability, which is consistent with our findings.

[6] In comparison with Chordia et al. (2016), our dataset is more comprehensive, containing more than 3 million bond-month observations even after excluding matrix prices, while their data include approximately 1 million bond-month observations including matrix prices. Since most bond pricing before 1978 is matrix pricing in the Lehman Brothers database, our sample starts in 1979. Chordia et al. (2016) also employs the Lehman Brothers database and their sample runs from 1973, because they include matrix pricing in their data.

bonds in the cross section. Our results are also consistent with Kapadia and Pu (2012), who show that CDS and equity prices can diverge frequently. Collin-Dufresne et al. (2001) suggest that CDS spread changes are driven mainly by supply/demand shocks rather than by structural credit model variables. Duarte et al. (2007) document that capital structure arbitrage, which exploits relative pricing between equity and CDS contracts of the same underlying assets, is a highly profitable strategy among many fixed income arbitrage strategies. Bao and Hou (2013) find that their extended Merton model can explain comovement between equity and bonds. We contribute to this literature by examining the joint cross section of equity and bond returns.

2.2 Data

2.2.1 Corporate Bond Data

The main database for corporate bonds is the Reuters Fixed Income Database (previously known as the EJV database), which collects quotes provided by major dealers in corporate bond markets as of 3 p.m. ET each day.[7] The database provides daily quotes, terms and conditions, and historical amounts outstanding for the period running from 1991 through 2012. For the earlier sample period from 1979 through 1991, we employ the Lehman Brothers Fixed Income database for corporate bond prices. We eliminate matrix prices from both price databases because, as noted by Warga and Welch (1993), matrix prices do not reflect firm-specific information. The original sample period of the database begins in 1973, but after the elimination of matrix pricing, it starts in 1979. In addition to these two bond price databases, we use the Mergent Fixed Income Security Database for information on detailed terms and conditions.

The Thomson Reuters pricing data that we use provide advantages over previous databases employed in the literature. In particular, it is a comprehensive database covering more than 500,000 corporate bonds and thus enables us to perform a thorough study of the cross section of corporate bonds. In comparison, previous datasets in the literature cover only a smaller subset of outstanding bonds. For example, transaction data from the Trade Reporting and Compliance Engine (TRACE) and the National Association of Insurance Commisioners (NAIC) and specific bond data that comprise the Merrill Lynch corporate bond indices do not provide a comprehensive picture of the corporate bond universe. In contrast, the Thomson Reuters database is regarded by many major Wall Street firms as a standard database for marking their books mainly because of the wide coverage of the cross section of corporate bonds.

Also note that the pricing data provided by Reuters are mainly dealer quotes. Dealer quotes can be stale and might not necessarily reflect actual transaction prices. Choi (2013) and Choi and Richardson (2016) also employ the Reuters corporate bond pricing data and perform a battery of

[7] For a detailed description of the Reuters database, see Choi (2013) and Choi and Richardson (2016).

tests of the quality of the data.[8] Their main conclusion is that at the monthly frequency dealer quotes in the Reuters data reflect transaction-based prices quite well and price staleness is not severe. Following these studies, we also employ month-end prices for our study.

2.2.2 Constructing the Firm-Level Bond Return Sample

To study equity and bond returns jointly, we match corporate bonds to stocks of the same company. The first step is to use issuer-level six-digit cusips for each stock in the CRSP/Compustat universe and match bonds with the same issuers. We further identify bonds issued by subsidiaries using issuer information available in the FISD database. In addition, we keep track of surviving firms in the case of mergers and acquisitions and match bonds originally issued by acquired bonds to surviving firms, using the CRSP event file, because surviving firms will have different issuer-level cusips from acquired firms.

We take several measures, in addition to the data quality check provided in Choi (2013) and Choi and Richardson (2016), to ensure that our results are not driven by illiquid bond issues. First, we use *firm*-level bond returns by value-weighting individual bond returns issued by the same firms. Since bonds with greater amounts outstanding are likely to be traded more often and their prices are therefore likely to be more up to date, this value-weighting at the firm level will minimize any potential stale price issue for small illiquid bonds. Furthermore, as shown in Bao and Pan (2013), using firm-level bond returns as opposed to individual bond returns significantly reduces noise in individual bond prices arising from illiquidity issues. In addition, we use monthly bond returns measured at each month's end, as they ensure more accurate prices because dealers check their books more carefully when they conduct month-end closing (Warga and Welch (1993)).

To further ensure that our results are not driven by small illiquid issues, we eliminate bonds with small issue amounts (less than \$1MM). In addition, we apply more aggressive bond amount filters used by Barclays U.S. Corporate Index (also called "liquidity constraint" according to Barclays) to further ensure that only bonds that are large and liquid enough to be included in the index populate our sample.[9] We also exclude short-term bonds with less than one year of time to maturity as well as convertible bonds, because they have equity price components.

We calculate monthly returns on individual bonds using dirty prices:

$$R_{t+1}^{bond} = \frac{P_{t+1} + AI_{t+1} + C_{t+1} - (P_t + AI_t)}{P_t + AI_t} \tag{2.1}$$

where P_t is the quoted price, C_t is the coupon, and AI_t is the accrued interest. Firm-level bond returns are obtained by value-weighting individual bond returns using previous months' market

[8] For example, see Table A.I in the Online Appendix of Choi (2013) and also Tables A.1 through A.3 in Choi and Richardson (2016).

[9] Since the Barclays Aggregate Corporate Bond Index began in 1973, it has raised the liquidity constraint from \$1MM to \$25MM on Aug 1, 1988; to \$50MM on Jan 1, 1990; to \$100MM on Jan 1, 1994; to \$150MM on July 1, 1999; to \$200MM on Oct 1, 2003; and finally to \$250MM on July 1, 2004. We follow these liquidity constraints as bond amount filters.

values.

2.2.3 Sample Summary Statistics

We obtain the main sample by merging the aforementioned corporate bond databases with the CRSP/Compustat databases. After eliminating matrix pricing, the sample spans the period from July 1979 through May 2012 covering 3,498 firms with 3,175,253 bond-month and 321,598 firm-month observations.

Panel A of Table 2.1 provides the summary statistics of the firm-level sample across issuer-level ratings. The sample is skewed toward larger and levered firms, because we require firms to have bonds outstanding to be included in the sample. Higher-rated firms are larger and have more bonds outstanding. For example, AA-rated firms on average have 2.92 billion dollars in corporate bonds, while BB-rated firms have 0.80 billion dollars in corporate bonds. Our sample coverage compared with the CRSP/Compustat universe is fairly high, especially for investment-grade firms for which, on average, around 80% to 88% of the CRSP/Compustat universe in terms of stock market capitalization is covered by our sample. Our bond-level sample covers 70%-85% of bond amounts in the FISD database, as can be seen from Panel B, also showing that the coverage of our bond price database is very high compared with the more comprehensive FISD database.

2.3 Cross Section of Corporate Bond Returns

Among many cross-sectional predictors, we focus on asset growth (AG), investment-to-assets (IA), gross profitability (GP), and net issuance (NI).[10] We choose these variables due largely to recent interest shown in the literature.[11]

In addition to these cross-sectional predictors, we also examine such traditional ones as book-to-market (BM) and momentum (MOM) as well as idiosyncratic volatility ($IVOL$), equity beta ($BETA$), and accrual ($ACCR$).[12]

[10] Asset growth (AG) is year-on-year percentage change in total assets, following Cooper et al. (2008). Investment-to-assets (IA) is measured as the annual change in gross property, plant, and equipment plus the annual change in inventories scaled by the lagged book value of assets (Li et al. (2009)). We use gross profitability (GP) as revenues minus cost of goods sold divided by lagged assets as in Novy-Marx (2013). Net issuance (NI) is the growth rate of the split-adjusted shares outstanding in the previous fiscal year (Pontiff and Woodgate (2008)).

[11] For example, Fama and French (2008c) and Fama and French (2008a) analyze these anomalies in greater detail.

[12] Idiosyncratic volatility ($IVOL$) is the standard deviation of return residuals from the Fama and French (1993) three-factor model following Ang et al. (2006). Beta ($BETA$) is obtained from rolling regressions of excess equity returns on market excess returns using 3-year rolling window. Accrual ($ACCR$)is the changes in non-cash working capital minus depreciation expense scaled by lagged asset (Sloan (1996)).

2.3.1 Portfolio-Level Results

We sort firms into decile portfolios using the nine cross-sectional predictors for the period running from 1979 through 2012. Every end of June, firms are ranked using information available at the end of the previous year. We form both equal- and value-weighted (EW and VW) portfolios of monthly bond returns. The equal-weighted portfolios are obtained by equally weighting firm-level bond returns that are value-weighted individual bond returns within each firm. Thus, the equal-weighted portfolios weight each firm, not each bond, equally. We employ this firm-level equal-weighting to prevent small, illiquid bond issues from driving our results, following Bao and Pan (2013). The value-weighted portfolios weight returns using the previous months' bond market values at each firm. We also form corresponding equity portfolios using the same set of firms to ensure that cross-sectional equity return patterns documented in previous studies also appear in our sample of firms.

Table 2.2 provides the average returns and alphas of low (L) and high (H) decile portfolios. We start in Panel A with sorts on AG. We find in our sample an asset growth effect in equity portfolios. The high-minus-low (HL) equity return is large (-0.98% per month) and highly statistically significant in the EW portfolio, although the alpha decreases and becomes statistically insignificant in the VW portfolio.[13]

We report a significant asset growth effect among bond returns. For example, the average HL returns are -0.32% and -0.21% monthly for the EW and VW portfolios, respectively, both of which are highly statistically significant with a t-statistic of -5.30 and -4.03. This asset growth effect at the bond level is not subsumed by common risk factors such as the Fama-French three factors (R^{MKT}, R^{SMB}, and R^{HML}) or bond factors (R^{TERM} and R^{DEF}).[14] The alphas of HL portfolios are -0.32% and -0.17% monthly for the EW and VW portfolios, respectively, and are highly statistically significant. Furthermore, these alphas are not driven by small, illiquid bonds, since we find consistent results when we apply the liquidity filter based on the Barclays Index inclusion rule, as shown in the bottom rows of each panel.[15]

In Panel B, portfolios sorted on IA exhibit results similar to those found for the AG portfolios. High IA portfolios earn lower bond returns than low IA portfolios. The HL excess return is -0.24% per month for the equal-weighted portfolios, which is roughly a third of that of equity portfolios and also statistically significant at the 1% level. The results are robust to exclusion of small illiquidity bond issues when we apply the liquidity constraint filter of the Barclays Index. In column four, the HL portfolio alphas are all statistically significant at the 1% level even when the value-weighted alpha of equity returns is not statistically significant, suggesting that the investment anomaly is even stronger at the bond level. We confirm that the investment anomaly exists in corporate bond

[13] Cooper et al. (2008) and Fama and French (2008c) also report that the asset growth anomaly is stronger among small firms.

[14] The term factor R^{TERM} is the return on 30-year Treasury bonds minus the return on 1-year Treasury bonds and the default factor R^{DEF} is the return on an equally weighted market portfolio of all corporate bonds with at least one year to maturity minus the return on Treasury bonds, following Acharya et al. (2013).

[15] See footnote 9 for the the liquidity constraint rule of the Barclays Index.

returns.

In Panel C (GP), we find divergent patterns in portfolio returns between equity and bonds. Equity returns exhibit the gross profitability premium. Although the average returns for the HL portfolio is not positive, its alpha reported in column four is positive and statistically significant. In the VW portfolio, for example, the alpha is 0.80% per month with a t-statistic of 3.84. This result is consistent with Novy-Marx (2013), who also finds that the gross profitability premium becomes much larger when controlling for the Fama-French factors. In contrast, we find no evidence for the gross profitability premium in the bond portfolios. The average returns or alphas of HL portfolios are close to zero and not statistically significant. These results show that GP, although a firm-level rather than equity-level variable, is associated only with equity returns.

In relation to our findings, Chordia et al. (2016) argue that profitability is negatively related to corporate bond returns, a result that seems the opposite of what Novy-Marx (2013), who shows that gross profitability is positively related to equity returns, finds. Note first that they use profitability instead of *gross* profitability. As their footnote 10 says, they also find weak results when using gross profitability, consistent with our results. We further investigate this issue in Section 2.3.2 using Fama-MacBeth regressions. In short, our Fama-MacBeth regressions show that the result in Chordia et al. (2016) is driven mainly by small bonds. Moreover, their results are based on *individual* bond returns as opposed to firm-level bond returns. Our portfolio results in Table 2.2 Panel C are based on firm-level bond returns that are value-weighted within each firm and thus are likely to be less sensitive to noise issues arising from illiquidity (Bao and Pan (2013)).

In Panel D, we find only small NI effects in bond returns. Average returns on HL portfolios are not statistically significant. Although value-weighted bond returns generate a negative and significant alpha (-0.13% per month), the magnitude is rather small. Moreover, the HL alpha further decreases to -0.11% per month when small bonds are excluded from the sample using the Barclays index inclusion rule. Overall, we do not find strong support for the net issuance effect among corporate bond returns.

In Panels E and F, we report results based on BM and MOM portfolios.[16] We find the value effect in EW portfolios for both equity and corporate bond returns, although the effect is statistically insignificant in value-weighted portfolios. In estimating alphas, we exclude the HML factor to avoid subsuming the value effect in corporate bond returns. In Panel F, we find strong momentum effects in bond portfolios, consistent with Jostova et al. (2013). Both average returns and alphas are economically and statistically significant.

Lastly, we provide portfolio results sorted on $BETA$, $IVOL$, and $ACCR$ in Panel G, H, and I, respectively. We find no reliable relation between these variables and future bond returns for $BETA$ and $ACCR$. In comparison, we find weak evidence for the positive idiosyncratic volatility effect in bond returns in contrast to evidence found in equity returns (Ang et al. (2006)).[17] For example,

[16] Book-to-market (BM) is the ratio of book equity to market equity, following Fama and French (1992), and momentum (MOM) is cumulative equity returns of the past 12 months. MOM is measured each month and used for portfolio sorting as in Jegadeesh and Titman (1993).

[17] Chordia et al. (2016) also document a positive relation between idiosyncratic volatility and bond returns.

the alpha on the equal-weighted bond portfolio is 0.13% per month, although the alphas become insignificant for the value-weighted portfolios or when the liquidity constraint filter is applied to remove small illiquid bonds.

In summary, the results for corporate bond portfolios show that asset growth, investment, and momentum are reliably priced in the cross section of bonds, while we find no strong support for profitability, net issuance, beta, idiosyncratic volatility, or accrual.

2.3.2 Fama-MacBeth Regression Results

The results based on portfolio sorts in Table 2.2 do not control for other characteristics that might affect corporate bond returns. In this section, we employ the standard Fama-MacBeth regression approach to control for both bond- and firm-level characteristics.

As control variables in bond return regressions, we include proxies for credit risk and liquidity in addition to the equity-level control variables. Specifically, we include log market leverage ($log(D/A)$) and asset volatility estimated using the past 36 months of asset returns.[18] Since trading-based liquidity proxies for individual bonds are not available for our sample, we include multiple proxies for liquidity, following Longstaff et al. (2005). The first proxy is the log amount outstanding of each bond, because large bonds are more liquid. To capture a potential on-the-run versus off-the-run effect, we include the ages of bonds in years. The last liquidity proxy is time to maturity, because liquidity can be affected by investor clientele (Mahanti et al. (2008) and Huang et al. (2014)). Time to maturity will also control for the term premium. We value-weight these bond-level controls for each firm using market values and perform the Fama-MacBeth regressions using firm-level bond returns instead of individual bond returns to avoid driving the results mainly by small bonds.

Panel A in Table 2.3 reports the Fama-MacBeth regression results for excess bond returns. The results are largely consistent with those obtained from portfolio returns, reported in Table 2.2. AG and IA are negatively related to bond returns and the corresponding coefficients are highly statistically significant when they are considered individually (columns 1 and 2), although only IA is statistically significant when considered together (column 11). For GP, however, the coefficient estimate is not statistically different from zero. Similarly, the coefficient on NI is negative but is not statistically significant. Both BM and MOM are strongly positively related to cross-sectional bond returns whereas $BETA$ and $ACCR$ are not related to bond returns. $IVOL$ is positively related to bond returns when considered individually, but it becomes insignificant when all variables are included in the specification.

To check robustness, we further control for maturity and credit risk by using abnormal bond returns, following Bessembinder et al. (2009) (BKMX), as shown in Panel B. The results are

[18] We calculate monthly asset return series for each firm following the procedure in Choi (2013) and Choi and Richardson (2016). In short, asset returns are value-weighted averages of equity, corporate bond, and bank loan returns.

largely similar to those shown in Panel A, except that GP is negative and statistically significant in column 3 of Panel B. In Panel C, we investigate further whether these results are robust to the exclusion of small, potentially illiquid bonds, using the Barclays Index inclusion rules. We find that the coefficients on GP is no longer statistically significant and the economic magnitude is also smaller in Panel C. Thus, gross profitability is largely a small bond effect.

In summary, the results lead to a conclusion that is similar to the conclusion derived from the portfolio-level results. Investment and momentum anomalies exist among bond returns, whereas we find no strong support for profitability, net issuance, beta, or accrual anomalies.

2.4 Anomalies in the Joint Cross Section of Equity and Corporate Bonds

The previous section documents that many of the anomaly variables tend not to predict corporate bond returns. An interesting and important question that arises is whether these discrepancies in the joint cross section of returns can be explained by the sensitivity of debt to equity, or hedge ratios. If the mechanism of anomalies operates through the value of underlying firms' assets, cross-sectional corporate bond returns should be consistent with their hedge ratios and the corresponding equity returns. We examine this issue in this section.

2.4.1 Economic Framework and Methodology

Consider a contingent claim pricing framework in which a firm's asset process A_t follows a geometric Brownian motion and is the state variable determining equity $E(A_t)$ and bond $B(A_t)$ values. It is a standard result that an (instantaneous) expected return on the bond μ_B is related to an expected return on equity μ_E through $\mu_B - r = \frac{\partial B}{\partial E}\frac{E}{B}(\mu_E - r)$ where r is the risk-free rate and the partial derivative $\frac{\partial B}{\partial E}\frac{E}{B}$ is the sensitivity of the bond to equity, or hedge ratio h.[19] In approximation, we obtain

$$R^B_{t+1} \approx \frac{\partial B/B}{\partial E/E} R^E_{t+1} \equiv h R^E_{t+1}. \tag{2.2}$$

where $R^B_{i,t+1}$ and $R^E_{i,t+1}$ are excess returns on corporate bond and equity portfolios of same underlying firms. Assuming the hedge ratio is constant,[20] we can rewrite the above equation in terms of expected returns:

$$E[R^B_{t+1}] \approx h E[R^E_{t+1}]. \tag{2.3}$$

Equations (2.2) and (2.3) summarize how equity and corporate bonds are linked through changes in the value of underlying firms' assets. Expected bond returns are determined by hedge ratios

[19] In general, the equation $\mu_B - r = \frac{\partial B}{\partial E}\frac{E}{B}(\mu_E - r)$ holds as long as A_t is the only state variable for equity and bonds. Suppose the process for A_t is $dA_t/A_t = \mu dt + \beta W_{Mt} + \sigma_I W_{It}$ where the two independent, standard Brownian motions dW_{Mt} and dW_{It} represent systematic and idiosyncratic shocks whose prices of risk are λ and 0, respectively. Then, it can be shown that the expected excess returns on equity $E(A_t)$ and bond $B(A_t)$ are given as $\mu_E - r = \frac{\partial E}{\partial A}\frac{A}{E}\beta\lambda$ and $\mu_B - r = \frac{\partial B}{\partial A}\frac{A}{B}\beta\lambda$.

[20] We will consider time-varying hedge ratios in Section 2.4.3.1.

and expected returns on the equity of the same firms. In other words, the high-minus-low bond portfolio returns reported in Table 2.2 should be close to the corresponding equity portfolio returns scaled by the hedge ratios.

In this regard, our baseline test is based on the following model:

$$R^B_{i,t+1} = \alpha_i + h_i R^E_{i,t+1} + \epsilon_{i,t+1} \tag{2.4}$$

The loading h captures how sensitive corporate bonds are with respect to equity and is our estimate of hedge ratios. The intercept α captures corporate bond return premia that cannot be explained by value changes in issuing firms' assets. Schaefer and Strebulaev (2008) show that the parametric model of hedge ratios based on the structural models of credit risk describes h well. In Section 2.4.3.1, we also consider time-variation in h using the structural models of credit risk like Schaefer and Strebulaev (2008), and our conclusion remains largely the same.

In our empirical implementation, we estimate $R^B_{i,t+1} = \alpha_i + h_{1i} R^E_{i,t+1} + h_{2i} R^E_{i,t} + \epsilon_{i,t+1}$ by also including lagged equity returns R^E_t in the estimation of (2.4), because bond prices might respond to equity prices with delay. The hedge ratio estimates are then $h_{1i} + h_{2i}$. The estimation of α is largely robust whether or not including lagged equity returns.

2.4.2 Results

Table 2.4 provides the estimation results for high-minus-low (HL) portfolios sorted on the cross-sectional predictors. We report results only for the value-weighted portfolios, since the results based on equal-weighted portfolios are largely similar.

In the first columns of Table 2.4 across the anomaly variables, we find that the estimated hedge ratios are fairly small, typically less than 0.10. For the anomaly variables except for MOM and $ACCR$, the hedge ratio estimates (the sum of the coefficients h_1 and h_2) range from -0.01 to 0.10. For MOM and $ACCR$, we obtain 0.15 and 0.16, respectively. These magnitudes of hedge ratio estimates imply that typically less than 10% of equity returns appear in bond returns through changes in firms' asset values. Take the NI portfolio, for example. The estimate for the hedge ratio is only 0.03, showing that only 3% of high-minus-low equity return premia translate to bond return premia. Combined with the VW high-minus-low equity returns on the NI portfolio (-0.57%) reported in Table 2.2, this hedge ratio estimate shows that the average return on the bond portfolio is expected to be approximately $-0.02\%(\approx 0.03\cdot -0.57\%)$ per month, which explains why the alpha estimate of the NI portfolio in Table 2.4 is fairly small and statistically indistinguishable from zero. We find similar results for the other portfolios, namely, GP, $BETA$, $IVOL$, and $ACCR$.

These results raise an important point. Considering the fairly low hedge ratios of those anomaly portfolios, we should not expect to observe significant effects of the equity-level anomaly variables on corporate bond returns. Typically, only less than 10% of cross-sectional equity return premia show up in the corresponding bond return premia. Thus, the divergent patterns in the joint cross section of returns shown in Table 2.2 are actually consistent with contingent claim pricing.

On the other hand, we find that alpha estimates are statistically significant for AG, IA, and MOM. For example, the estimates of α are -0.15%, -0.14%, and 0.19% per month for the AG, IA, and MOM portfolios, respectively, which are also statistically significant at the 5% level. In other words, the estimated hedge ratios in the first columns are too small to explain the observed bond return premia. For AG, the average return on the high-minus-low VW equity portfolio is -0.45% per month, as reported in Table 2.2. Given the low estimates of the hedge ratio (0.07), the equity return channel accounts for only $-0.03\%(\approx 0.07 \cdot -0.45\%)$ per month, while the average return on the bond portfolio (-0.19%) is much higher. Thus, the observed bond return premia of the AG, IA, and MOM portfolios tend to be too large compared with their sensitivity to equity returns, which manifest as significant nonzero alphas.

As a robustness check, we control for common risk factors in Table 2.4, since these alphas can be due to exposure to systematic risk that works through channels other than changes in firms' asset values. We employ the set of investment- and valuation-based factors of Fama and French (2015) as well as the Carhart four factors, since these factors are designed to explain equity portfolios sorted on AG, IA, and MOM. As for bond factors, although there is much less consensus as to what factors to use, most existing studies employ the two-factor model (i.e., default and term) suggested by Fama and French (1993).[21] In addition, we include liquidity factors for equity (Pastor and Stambaugh (2003)) and corporate bonds (Lin et al. (2013)).[22]

In the second and third columns of AG, IA, and MOM in Table 2.4, the non-zero α estimates are not subsumed by adding standard factor returns. The alpha estimates do not change much from the first columns. These results suggest that the effects of AG, IA, and MOM on bond returns are independent of equity markets. The results for MOM are also consistent with those in Jostova et al. (2013), which show that the momentum effect in corporate bonds is not a manifestation of momentum in equity. Although identifying the rational drivers of the bond-level AG and IA represent an interesting research question, we do not address this issue in this paper. Note also that these non-zero α estimates do not imply that any investors can implement a profitable trading strategy. The strategy involves short sales and incurs security borrowing costs.[23] Round trip transaction costs can be as high as 1.16% (Bao et al. (2011)). Given that the estimates of alphas for AG, IA, and MOM are only around 2% per year, it is not likely that they provide particularly profitable investment opportunities.

Overall, the results provided in Table 2.4 show that the divergent patterns in the joint cross section of returns are in fact consistent with contingent claim pricing. The main reason for this is that hedge ratios tend to be fairly small and typically less than 0.10, implying that most equity-level

[21] E.g., Gebhardt et al. (2005a), Gebhardt et al. (2005b), Acharya et al. (2013), and Jostova et al. (2013).

[22] Lin et al. (2013) construct corporate bond liquidity factors using the method of Pastor and Stambaugh (2003). We construct a factor-mimicking portfolio for our sample period by regressing the corporate bond liquidity factors on corporate bond portfolios sorted on five rating notches (AAA, AA, A, BBB, and high yield) by two maturity buckets. We employ the mimicking portfolio in our estimation of (2.4).

[23] Asquith et al. (2013) report that borrowing fees for corporate bonds are typically around 25 basis point annually.

anomaly variables are not likely to explain corporate bond returns.

2.4.3 Robustness Checks Using Hedge Ratios from the Merton Model

In this section, we provide a robustness check by directly estimating time-varying hedge ratios h_t. The rationale for this approach is also based on recent empirical evidence in the literature. Schaefer and Strebulaev (2008) document that hedge ratios derived from the Merton model fairly well explain the relationship between individual equity and bonds. By estimating h_t directly, we can also control for time variation in hedge ratios and thus corroborate the results in Section 2.4.2.

2.4.3.1 Estimating Hedge Ratios

We use the Merton model in estimating hedge ratios, following Schaefer and Strebulaev (2008). Specifically, the hedge ratio h is given as $\frac{1}{N(d_1)} - 1$ where $d_1 = \frac{log(A/F)+(r+\sigma^2/2)T}{\sigma\sqrt{T}}$ where A is the market value of assets, F is the face value of the bond, r is the risk-free rate, σ is the volatility of firms' assets, and T is the time-to-maturity of the bonds. A high hedge ratio implies that a bond price varies greatly with the firm's asset value and thus that the bond is equity-like.[24]

2.4.3.2 Results

Using hedge ratios, we examine returns on bond portfolios that are hedged against equity portfolio risk of the same firms. That is, we calculate the difference between bond returns and equity returns multiplied by hedge ratios $R^B_{t+1} - h_t R^E_{t+1}$. As shown in (2.3), this difference will be close to zero if underlying asset value changes drive most variation in equity and bond returns. Since additional priced factors can drive bond returns relative to equity returns, we also control for risk factors commonly used in the literature, as in Section 4.1.

Table 2.5 reports estimated hedge ratios h_t and the returns on the hedged portfolio $R^B_{t+1} - h_t R^E_{t+1}$ for the portfolios sorted on the nine cross-sectional predictors shown in Panels A through I. Note first that the estimated hedge ratios of the low (L) and high (H) decile portfolios are similar, indicating that cross-sectional heterogeneity in hedge ratios is not strong and thus is not likely the main driver of cross-sectional differences in equity and bond return patterns. These hedge ratio estimates from the Merton model are in magnitudes comparable to those reported in Schaefer and Strebulaev (2008).

The results using hedge ratios lead largely to the same conclusion as those reported in Table 2.4. Specifically, we find that returns on the VW hedged portfolios $R^B_{t+1} - h_t R^E_{t+1}$ for the GP, NI, BM,

[24] We use market leverage (A/F) from market equity plus book debt divided by book debt, time-to-maturity (T) from the weighted average of individual bond maturities for each firm, the risk-free rate (r) from the one-year Treasury rate, and asset volatility (σ) estimated using the past 36 months of asset returns following Choi (2013). We also use asset volatility estimated using a procedure that follows Bharath and Shumway (2008). The results are qualitatively the same.

$BETA$, $IVOL$, and $ACCR$ portfolios are statistically indistinguishable from zero. We find similar results for EW portfolios, except the alphas of $BETA$, $IVOL$, and $ACCR$ are 0.12%, 0.18%, and -0.09% per month, respectively, and statistically significant at the 5% or 10% levels. However, given that EW portfolios require the monthly rebalancing of small, illiquid corporate bonds, these alpha estimates are not likely to be economically meaningful. We conclude that the results are qualitatively similar to those shown in Table 2.4 in that the patterns in the joint cross section are consistent with contingent claim pricing.

Also similar to the results in Table 2.4, returns on the VW hedged portfolios sorted on AG, IA, and MOM are significantly different from zero and cannot be explained by exposures to standard risk factors. In particular, the average returns on the MOM portfolio is 0.31% per month and statistically significant at the 1% level. These results suggest that the bond-level effect of AG, IA, and MOM is too large to be explained by the changes in underlying firm values and is potentially driven by factors that work independently of equity markets. Overall, our results documented in Table 2.5 are consistent with those provided in Table 2.4.

2.5 Investor Sentiment, Business Cycles, and Cross-Market Return Premia

The previous section documents substantial investment and momentum effects in bond returns that are difficult to be reconciled with hedge ratios. In this section, we investigate the role of behavioral forces as a potential driver of those effects. Our analysis is motivated by Stambaugh et al. (2012), who find that investor sentiment drives overpricing in the short side of long-short strategies exploiting anomalies. In particular, we examine whether returns on corporate bonds hedged against equity risk of the same firms can be predicted by the sentiment index of Baker and Wurgler (2006) or business cycle variables that predict the market risk premium.[25]

2.5.1 Predictive Regression of Hedged Bond Returns: Fama-MacBeth Approach

We extend the standard Fama-MacBeth regression as follows. In the first stage, we run the cross-sectional regressions of corporate bond returns that are hedged against the equity risk of the same underlying firms ($R^B_{i,t+1} - h_{i,t}R^E_{i,t+1}$) for each time period t:

$$R^B_{i,t+1} - h_{i,t}R^E_{i,t+1} = a_t + \lambda_t X_{i,t} + \text{ctrls}_{i,t} + e_{i,t+1} \tag{2.5}$$

where $h_{i,t}$ is the hedge ratio for the portfolio i and $X_{i,t}$ is one of the nine cross-sectional predictors under consideration (i.e., AG, IA, GP, NI, BM, MOM, $BETA$, $IVOL$, or $ACCR$). The control variables ($ctrls$) are used in the literature to explain corporate bond returns. For example, we

[25]We thank Jeff Wurgler for making the sentiment data available on his website. The index is constructed as the first principal component of the closed-end fund discount, the number and the first-day returns of IPOs, the turnover in the NYSE, the equity share in total new issues, and the dividend premium.

include log market leverage, asset volatility, log amount outstanding of bonds, bond age, and time to maturity.

In the second stage, we regress the first-stage coefficient estimate λ_t on a constant, investor sentiment S_t, and business cycle variables Z_t:

$$\lambda_t = \alpha + \beta S_t + \gamma Z_t + \epsilon_{i,t} \tag{2.6}$$

The sentiment and business cycle variables are standardized for easier interpretation of the constant term and their economic significance. The constant term will capture the average return premia associated with the anomaly variables. The coefficients on S_t and Z_t capture how the return premium associated with each anomaly variable $X_{i,t}$ varies with sentiment and business cycles. The second-stage regression of the usual Fama-MacBeth approach corresponds to regressing on the constant term alone. For business cycle variables Z_t, we use the so-called standard instruments (dividend yields, term spreads, default spreads, T-bill rate, and the VIX).[26] The standard instruments disentangle the effect of investor sentiment from that of time variation in the market risk premium driven by business cycles.

Table 2.6 provides the regression results for (2.6). We find that bond-equity relative return premia, as captured by $R^B_{i,t+1} - h_{i,t}R^E_{i,t+1}$, tend to intensify with investor sentiment for most of the anomalies considered. In the AG and IA results, the coefficient estimates on sentiment S_t are negative, indicating that the asset growth and investment effects on bond returns relative to equity returns become stronger when sentiment is higher. This result is not likely due to business cycles, since both the statistical and economic significance of the coefficient estimates on sentiment are stronger when the standard instruments are included. For the GP, NI, BM, $IVOL$, and $BETA$ anomalies, we also find that higher sentiment tends to increase the differences in relative return premia between equity and corporate bonds, although their statistical significance decreases when controlling for the standard instruments.

More importantly, the signs of the sentiment coefficients for these anomalies indicate that the anomaly variables tend to predict hedged corporate bond returns as they predict equity returns. For example, the coefficients on sentiment for $BETA$ and $IVOL$ are negative, indicating that when investor sentiment is high, corporate bonds with high equity beta or high idiosyncratic volatility earn lower returns. These results suggest that behavioral forces at least partly drives anomaly effects on the cross-sectional corporate bond returns.

[26]The dividend yield is based on Fama and French (1988), the term spread is 10-year Treasury constant maturity minus one-year Treasury constant maturity yields, the default spread is the difference between BAA and AAA corporate bond yields from the Federal Reserve, the T-bill rate is the one-month T-bill rate, and the VIX is a measure of implied volatility calculated using 30-day S&P 100 index at-the-money options from the Chicago Board Options Exchange (CBOE).

2.5.2 Predictive Regression of Relative Return Premia: Long vs. Short Portfolio Approach

In this section, we further investigate the sentiment effect on corporate bonds by separating long and short legs of trading strategies exploiting anomalies. Specifically, we estimate the following model for the long and short sides of value-weighted decile portfolios:

$$R^B_{i,t+1} - h_{i,t}R^E_{i,t+1} = a_0 + a_1 S_t + a_2 Z_t + e_{i,t+1}. \tag{2.7}$$

As in the previous Fama-MacBeth regression in (2.6), S_t and Z_t are standardized and thus the constant term a_0 captures average returns on corporate bond portfolios hedged against equity risk and a_1 and a_2 capture their variation due to investor sentiment and business cycles, respectively. Stambaugh et al. (2012) argue that if mispricing amplifies anomalies, abnormal returns should be greater on the short side when sentiment is high, because of short-sale impediments. Similarly, if the difference in relative return premia is related to overpricing in corporate bonds, we expect to see a_1 show up negatively, especially for the short portfolios.

As predicted, Table 2.7 shows that the expected returns on corporate bonds hedged against equity risk ($R^B_{i,t+1} - h_{i,t}R^E_{i,t+1}$) on the short side increases as investor sentiment becomes stronger. For example, the coefficient on investor sentiment is -0.29% on the short side of the AG portfolio. We find similar results for the IA, NI, BM, MOM, and $BETA$ portfolios. Taken together, we document the role of sentiment in bond returns, suggesting behavioral forces also drive the cross section of corporate bond returns along the dimension of anomaly variables.

2.6 Conclusion

We investigate the joint cross section of equity and corporate bond returns to determine the extent to which the relative return premia in the two markets are consistent with contingent claim pricing. First, we document which of the anomalies known in the equity pricing literature also exist in bond returns. The asset growth and investment anomalies exist in corporate bond markets, whereas the gross profitability, net issuance, low beta, accrual, and idiosyncratic anomalies are largely equity-only phenomena. Interestingly, we find that the non-existence of these anomalies in corporate bonds is in fact consistent with contingent claim pricing. In particular, the estimated sensitivities of debt to equity, or hedge ratios, are too small, typically less than 0.10, and thus less than 10% of equity return premia appear in corporate bond return premia, which explains why many equity-level predictors do not explain corporate bond returns. In addition, we document the investor sentiment effect in corporate bonds by showing that investor sentiment predicts differences in bond-equity return premia, especially on the short side of long-short strategies where short sales impediments are supposedly strong.

2.7 Figures and Tables

Table 2.1 Summary Statistics

This table reports sample summary statistics for eight issuer-level rating buckets. The sample includes firms with both equity and bond return data available from 1979 through 2012. We exclude matrix prices from the bond databases. Panel A reports firm-level summary statistics. Equity returns are measured as monthly excess returns available from CRSP and bond returns are measured as firm-level monthly excess returns by value-weighting individual bond returns from the same issuing firms available in the Lehman Brothers and Reuter's Fixed Income databases. *Market leverage* is the book debt divided by market equity plus book debt available in Compustat Annual. *Market equity* is market capitalization in billions of dollars from CRSP. *Market cap coverage* is the average fraction of total stock market capitalization of firms in our sample out of the total stock market capitalization of the CRSP/Compustat universe. *Firm-month obs.* is the total number of firm-month observations in the sample. Panel B reports bond-level summary statistics. *Bond amount* is the amount outstanding in billions of dollars for each bond. *Time to maturity* is the time-to-maturity in years for each bond. *FISD coverage* is the fraction of total bond amounts in our sample out of the total bond amounts of the FISD universe. *Bond-month obs.* is the total number of bond-month observations in the sample.

Panel A: Firm Level Statistics								
	AAA	AA	A	BBB	BB	B	CCC	Unrated
Mean equity return(%)	0.55	0.65	0.77	0.76	0.73	0.43	0.73	0.59
Stdev equity return(%)	9.89	7.68	8.80	10.28	14.22	20.26	31.01	15.67
Mean market leverage	0.21	0.29	0.32	0.35	0.43	0.55	0.71	0.43
Median market leverage	0.10	0.20	0.27	0.32	0.41	0.56	0.78	0.40
Mean market equity($bn)	87.49	25.16	13.32	5.98	2.19	1.04	0.58	1.56
Median market equity($bn)	44.11	7.47	5.04	2.69	0.97	0.37	0.11	0.61
Market cap coverage(%)	87.94	85.57	86.91	79.54	59.56	69.83	66.16	20.06
No. firm-month obs.	3,327	16,022	59,417	69,132	52,986	40,775	3,907	76,032
Panel B: Bond Level Statistics								
	AAA	AA	A	BBB	BB	B	CCC	Unrated
Mean bond return(%)	0.31	0.32	0.39	0.45	0.43	0.73	0.59	0.37
Stdev bond return(%)	1.94	2.01	2.75	4.31	20.26	31.01	15.67	5.96
Mean bond amount($bn)	4.70	2.92	2.49	1.52	0.80	0.69	0.79	0.49
Median bond amount($bn)	1.14	0.70	0.70	0.55	0.31	0.24	0.20	0.15
Mean time to maturity(Year)	12.87	12.89	11.78	10.71	8.41	7.53	6.46	11.94
Mean coupon(%)	6.54	7.54	7.20	7.15	8.03	8.63	8.82	8.11
Mean FISD coverage(%)	70.09	81.84	73.58	84.06	80.19	83.10	78.80	81.46
No. bond-month obs.	390,012	312,649	1,027,590	657,751	245,781	150,097	13,702	377,671

Table 2.2 Cross Section of Corporate Bond Returns: Portfolio Approach

This table provides average excess returns on equity and bonds and alphas for high and low decile portfolios sorted on nine cross-sectional variables. The sorting variables are asset growth (AG) (Panel A), investment-to-assets (IA) (Panel B), gross profitability (GP) (Panel C), net issuance (NI) (Panel D), book-to-market (BM) (Panel E), momentum (MOM) (Panel F), beta ($BETA$) (Panel G), idiosyncratic volatility ($IVOL$) (Panel H), and accrual ($ACCR$) (Panel I). Using these variables available at the end of the previous years, we sort equity and bonds into equal- and value-weighted decile portfolios in June of each year, except for the momentum portfolios. The momentum portfolios are sorted monthly based on six-months ranking and six-months holding periods, following Jegadeesh and Titman (1993). Monthly equal-weighted bond returns are measured by equally weighting firm-level bond returns, where the firm-level bond returns are value-weighted individual bond returns. *Equity* and *bond return* (the first and second rows in each subpanel) are measured as equity and bond returns minus the one-month T-bill rate, respectively. *Bond Return with Barclays Filter* is measured as bond excess returns after applying the liquidity constraint filter based on the Barclays U.S. Corporate Index inclusion rule. Alphas of the equity returns are estimated from the time-series regressions using the Fama-French three factors and alphas of bond returns are estimated using bond factors ($TERM$ and DEF) in addition to the Fama-French factors. We also report betas and R^2 for the high-minus-low portfolios. The sample period is from 1979 through 2012. *, **, and *** for the HL portfolio alphas denote statistical significance at the 10%, 5%, and 1% levels, respectively. The numbers in parentheses are t-statistics based on White (1980) robust standard errors.

Table 2.2 (con't.)

Panel A: Sorting on Asset Growth (AG)										
	L	H	HL	HL						
EW	Average Return			α	β^{MKT}	β^{SMB}	β^{HML}	β^{TERM}	β^{DEF}	R^2
Equity Return	1.01	0.03	-0.98***	-0.73***	-0.03	-0.34***	-0.61***			20.7%
	(2.67)	(0.08)	(-4.85)	(-4.22)	(-0.61)	(-3.85)	(-8.15)			
Bond Return	0.60	0.27	-0.32***	-0.32***	0.02	-0.02	-0.11***	0.05**	0.01	12.5%
	(5.27)	(2.27)	(-5.30)	(-5.35)	(1.09)	(-0.88)	(-3.51)	(2.26)	(0.16)	
Bond Return with Barclays filter	0.57	0.28	-0.29***	-0.27***	0.01	-0.03	-0.12***	0.05**	-0.01	13.3%
	(4.86)	(2.31)	(-4.90)	(-4.88)	(0.57)	(-1.35)	(-4.37)	(2.04)	(-0.18)	
VW										
Equity Return	0.66	0.20	-0.45**	-0.29	0.05	-0.26***	-0.50***			16.9%
	(2.40)	(0.72)	(-2.34)	(-1.61)	(1.11)	(-3.32)	(-6.13)			
Bond Return	0.42	0.20	-0.21***	-0.17***	0.00	-0.05***	-0.09***	0.00	-0.16**	13.3%
	(3.70)	(1.85)	(-4.03)	(-2.92)	(0.12)	(-3.08)	(-3.58)	(0.01)	(-2.32)	
Bond Return with Barclays filter	0.43	0.20	-0.22***	-0.18***	0.00	-0.06***	-0.10***	0.01	-0.12	11.4%
	(3.70)	(1.75)	(-3.95)	(-2.72)	(-0.13)	(-3.00)	(-3.22)	(0.53)	(-1.48)	
Panel B: Sorting on Investment (IA)										
EW	Average Return			α	β^{MKT}	β^{SMB}	β^{HML}	β^{TERM}	β^{DEF}	R^2
Equity Return	0.76	-0.02	-0.78***	-0.63***	0.02	-0.08	-0.47***			13.4%
	(2.23)	(-0.05)	(-3.89)	(-3.35)	(0.43)	(-1.13)	(-6.03)			
Bond Return	0.52	0.28	-0.24***	-0.24***	-0.01	-0.01	-0.10***	0.05**	0.30***	12.5%
	(4.85)	(2.29)	(-3.95)	(-3.91)	(-0.57)	(-0.28)	(-3.04)	(2.54)	(3.25)	
Bond Return with Barclays filter	0.51	0.28	-0.23***	-0.24***	0.00	0.00	-0.09***	0.04**	0.21**	11.4%
	(4.68)	(2.26)	(-4.13)	(-4.12)	(-0.09)	(0.08)	(-2.99)	(2.06)	(2.58)	
VW										
Equity Return	0.55	0.26	-0.29	-0.25	0.09*	-0.15*	-0.22***			16.9%
	(2.16)	(0.88)	(-1.49)	(-1.25)	(1.73)	(-1.96)	(-2.59)			
Bond Return	0.42	0.23	-0.19***	-0.23***	0.00	-0.01	-0.07**	0.09***	0.34***	13.4%
	(4.18)	(1.86)	(-2.94)	(-3.06)	(-0.09)	(-0.55)	(-2.10)	(3.67)	(3.31)	
Bond Return with Barclays filter	0.44	0.23	-0.20***	-0.25***	-0.01	-0.02	-0.07*	0.10***	0.37***	13.5%
	(4.21)	(1.80)	(-3.04)	(-3.13)	(-0.22)	(-0.93)	(-1.93)	(3.92)	(3.36)	

Table 2.2 (con't.)

	L	H	HL	α	β^{MKT}	β^{SMB}	β^{HML}	β^{TERM}	β^{DEF}	R^2
Panel C: Sorting on Gross Profitability (GP)										
	Average Return			HL						
EW										
Equity Return	0.75	0.75	0.00	0.41**	-0.30***	-0.17**	-0.73***			27.1%
	(2.12)	(2.71)	(0.00)	(2.22)	(-5.57)	(-2.22)	(-8.01)			
Bond Return	0.39	0.35	-0.05	-0.05	0.00	0.00	-0.03*	0.05**	-0.06	12.5%
	(4.03)	(3.54)	(-0.90)	(-0.97)	(-0.07)	(0.17)	(-1.76)	(2.25)	(-0.74)	
Bond Return after Liquidity Filter	0.39	0.33	-0.05	-0.03	-0.02	-0.01	-0.04*	0.01	-0.12	5.4%
	(3.64)	(3.28)	(-0.97)	(-0.42)	(-0.84)	(-0.27)	(-1.84)	(0.53)	(-1.30)	
VW										
Equity Return	0.44	0.58	0.14	0.80***	-0.58***	-0.16**	-1.04***			16.9%
	(1.24)	(2.63)	(0.55)	(3.84)	(-8.71)	(-2.28)	(-11.17)			
Bond Return	0.22	0.26	0.05	-0.01	0.00	-0.03*	-0.08**	0.15***	0.28**	19.1%
	(2.70)	(2.47)	(0.74)	(-0.10)	(-0.05)	(-1.93)	(-2.48)	(6.15)	(2.52)	
Bond Return after Liquidity Filter	0.24	0.27	0.03	0.01	0.00	-0.04*	-0.08**	0.10***	0.23*	9.1%
	(2.62)	(2.43)	(0.49)	(0.07)	(-0.17)	(-1.78)	(-2.31)	(3.49)	(1.77)	
Panel D: Sorting on Net Issuance (NI)										
EW	Average Return			α	β^{MKT}	β^{SMB}	β^{HML}	β^{TERM}	β^{DEF}	R^2
Equity Return	0.92	0.20	-0.72***	-0.85***	0.20***	0.28***	-0.08			19.5%
	(3.43)	(0.58)	(-4.16)	(-5.31)	(4.42)	(3.84)	(-1.22)			
Bond Return	0.38	0.34	-0.04	-0.07	0.05***	0.07***	-0.02	-0.06***	0.20***	12.5%
	(3.90)	(3.05)	(-0.73)	(-1.63)	(3.79)	(3.96)	(-1.25)	(-3.84)	(4.35)	
Bond Return after Liquidity Filter	0.35	0.34	-0.01	-0.04	0.05***	0.07***	-0.01	-0.05***	0.20***	36.6%
	(3.46)	(2.95)	(-0.28)	(-1.02)	(3.10)	(3.48)	(-0.79)	(-3.27)	(3.77)	
VW										
Equity Return	0.78	0.21	-0.57***	-0.64***	0.14***	0.00	-0.04			16.9%
	(3.32)	(0.79)	(-3.58)	(-3.82)	(3.12)	(-0.04)	(-0.49)			
Bond Return	0.30	0.22	-0.07	-0.13***	0.07***	0.03**	0.03	-0.02	0.19***	31.0%
	(2.96)	(1.97)	(-1.45)	(-2.72)	(4.76)	(2.08)	(1.29)	(-1.61)	(3.28)	
Bond Return after Liquidity Filter	0.29	0.23	-0.06	-0.11**	0.08***	0.03	0.04*	-0.05***	0.15**	27.3%
	(2.69)	(1.97)	(-1.07)	(-2.19)	(4.99)	(1.64)	(1.71)	(-2.70)	(1.99)	

Table 2.2 (con't.)

Panel E: Sorting on Book-to-Market (BM)										
	L	H	HL	HL						
EW	Average Return			α	β^{MKT}	β^{SMB}	β^{HML}	β^{TERM}	β^{DEF}	R^2
Equity Return	0.37	0.92	0.55**	0.56**	-0.11	0.34***				4.3%
	(1.19)	(2.54)	(2.13)	(2.17)	(-1.46)	(3.18)				
Bond Return	0.32	0.53	0.21***	0.20***	-0.05**	-0.01		-0.01	0.45***	18.2%
	(3.07)	(4.56)	(2.87)	(3.02)	(-1.99)	(-0.29)		(-0.45)	(4.35)	
Bond Return after Liquidity Filter	0.31	0.52	0.21**	0.18**	-0.04	0.01		-0.01	0.55***	23.0%
	(2.95)	(4.10)	(2.52)	(2.50)	(-1.46)	(0.32)		(-0.49)	(4.53)	
VW										
Equity Return	0.44	0.70	0.26	0.22	0.07	0.02				0.6%
	(1.91)	(2.37)	(1.12)	(0.93)	(1.15)	(0.21)				
Bond Return	0.28	0.36	0.08	0.07	-0.01	0.02		-0.05*	0.34***	21.8%
	(2.85)	(3.46)	(1.21)	(1.15)	(-0.65)	(1.33)		(-1.84)	(4.39)	
Bond Return after Liquidity Filter	0.30	0.36	0.06	0.05	0.00	0.03		-0.04*	0.26***	14.5%
	(2.91)	(3.47)	(0.96)	(0.85)	(-0.26)	(1.60)		(-1.72)	(3.07)	
Panel F: Sorting on Momentum (MOM)										
EW	Average Return			α	β^{MKT}	β^{SMB}	β^{HML}	β^{TERM}	β^{DEF}	R^2
Equity Return	0.08	1.00	0.92**	1.26***	-0.37***	-0.34*	-0.31			6.4%
	(0.16)	(3.09)	(2.29)	(3.36)	(-2.85)	(-1.66)	(-1.38)			
Bond Return	0.23	0.57	0.34***	0.41***	-0.04	-0.06	-0.01	0.00	-0.51***	13.4%
	(1.56)	(5.58)	(3.59)	(4.80)	(-1.41)	(-1.49)	(-0.21)	(0.11)	(-3.50)	
Bond Return after Liquidity Filter	0.22	0.53	0.31***	0.40***	-0.06**	-0.06	-0.01	0.01	-0.58***	25.0%
	(1.41)	(5.22)	(2.95)	(4.38)	(-2.02)	(-1.47)	(-0.24)	(0.28)	(-3.83)	
VW										
Equity Return	0.01	0.77	0.77**	1.04***	-0.37***	0.08	-0.26			5.2%
	(0.01)	(2.57)	(2.13)	(2.92)	(-3.44)	(0.42)	(-1.37)			
Bond Return	0.11	0.42	0.31***	0.32***	-0.06	-0.04	0.03	0.06*	0.01	4.0%
	(0.81)	(3.89)	(3.01)	(2.65)	(-1.54)	(-0.86)	(0.60)	(1.68)	(0.04)	
Bond Return after Liquidity Filter	0.10	0.40	0.30***	0.31***	-0.06*	-0.03	0.02	0.06*	-0.02	4.2%
	(0.74)	(3.68)	(2.86)	(2.61)	(-1.70)	(-0.59)	(0.53)	(1.75)	(-0.17)	

Table 2.2 (con't.)

Panel G: Sorting on Beta ($BETA$)										
	L	H	HL	HL						
EW	Average Return			α	β^{MKT}	β^{SMB}	β^{HML}	β^{TERM}	β^{DEF}	R^2
Equity Return	0.56	0.42	-0.13	-0.66***	0.88***	0.75***	-0.22*			57.6%
	(2.70)	(0.91)	(-0.37)	(-2.76)	(11.39)	(6.97)	(-1.90)			
Bond Return	0.37	0.44	0.06	-0.01	0.15***	0.14***	0.03	-0.16***	0.31***	55.8%
	(3.75)	(3.23)	(0.67)	(-0.21)	(6.14)	(5.65)	(0.85)	(-6.19)	(4.22)	
Bond Return after Liquidity Filter	0.34	0.42	0.08	-0.01	0.16***	0.13***	0.04	-0.16***	0.37***	56.6%
	(3.33)	(3.01)	(0.83)	(-0.09)	(6.17)	(4.79)	(1.30)	(-5.84)	(4.50)	
VW										
Equity Return	0.61	0.48	-0.13	-0.57**	0.91***	0.54***	-0.46***			59.0%
	(3.25)	(1.15)	(-0.36)	(-2.48)	(12.55)	(5.15)	(-3.60)			
Bond Return	0.32	0.27	-0.05	-0.03	0.12***	0.08***	0.02	-0.22***	-0.17	31.9%
	(2.94)	(2.57)	(-0.63)	(-0.39)	(4.18)	(3.04)	(0.52)	(-7.58)	(-1.23)	
Bond Return after Liquidity Filter	0.33	0.22	-0.11	-0.10	0.13***	0.08***	0.04	-0.23***	-0.26*	30.0%
	(2.93)	(2.04)	(-1.31)	(-1.12)	(4.73)	(3.04)	(1.14)	(-7.69)	(-1.95)	
Panel H: Sorting on Idio. Vol ($IVOL$)										
EW	Average Return			α	β^{MKT}	β^{SMB}	β^{HML}	β^{TERM}	β^{DEF}	R^2
Equity Return	0.73	0.35	-0.38	-1.03***	0.70***	1.24***	0.26*			50.3%
	(3.83)	(0.76)	(-1.01)	(-4.15)	(8.03)	(9.11)	(1.67)			
Bond Return	0.33	0.54	0.21*	0.13*	0.12***	0.17***	0.08**	-0.21***	0.43***	57.5%
	(3.27)	(4.08)	(1.92)	(1.79)	(4.66)	(6.23)	(2.17)	(-8.54)	(4.14)	
Bond Return after Liquidity Filter	0.34	0.53	0.19*	0.11	0.13***	0.16***	0.08**	-0.21***	0.47***	57.0%
	(3.23)	(3.81)	(1.72)	(1.44)	(5.20)	(5.72)	(2.08)	(-7.88)	(4.58)	
VW										
Equity Return	0.59	0.59	0.00	-0.51**	0.65***	0.88***	0.08			45.2%
	(3.13)	(1.45)	(0.00)	(-2.08)	(7.03)	(9.02)	(0.53)			
Bond Return	0.28	0.39	0.12	0.09	0.12***	0.16***	0.05	-0.20***	-0.04	33.4%
	(2.64)	(3.42)	(1.21)	(0.93)	(4.08)	(5.53)	(1.32)	(-6.58)	(-0.25)	
Bond Return after Liquidity Filter	0.28	0.39	0.11	0.08	0.13***	0.15***	0.07	-0.21***	-0.09	32.0%
	(2.55)	(3.35)	(1.13)	(0.86)	(4.33)	(4.96)	(1.62)	(-6.97)	(-0.62)	

Table 2.2 (con't.)

Panel I: Sorting on Accrual ($ACCR$)										
	L	H	HL	HL						
EW	Average Return			α	β^{MKT}	β^{SMB}	β^{HML}	β^{TERM}	β^{DEF}	R^2
Equity Return	0.50	0.36	-0.14	-0.12	-0.07*	-0.02	0.07			2.4%
	(1.37)	(1.08)	(-0.86)	(-0.73)	(-1.69)	(-0.25)	(1.20)			
Bond Return	0.41	0.36	-0.05	-0.06	0.00	0.04**	0.05**	0.00	-0.13**	6.0%
	(3.46)	(3.21)	(-0.94)	(-1.11)	(-0.06)	(1.97)	(2.53)	(0.16)	(-2.28)	
Bond Return after Liquidity Filter	0.40	0.38	-0.01	-0.02	-0.02	0.03	0.06**	0.03	-0.15**	12.4%
	(3.24)	(3.41)	(-0.26)	(-0.36)	(-1.43)	(1.55)	(2.39)	(1.54)	(-2.51)	
VW										
Equity Return	0.50	0.13	-0.37*	-0.34*	-0.02	0.04	-0.09			0.6%
	(1.68)	(0.44)	(-1.89)	(-1.70)	(-0.38)	(0.45)	(-1.06)			
Bond Return	0.26	0.32	0.05	0.08	-0.04**	0.05**	0.01	0.02	-0.19**	11.7%
	(2.02)	(2.79)	(0.90)	(1.29)	(-2.29)	(2.02)	(0.38)	(0.63)	(-2.29)	
Bond Return after Liquidity Filter	0.28	0.31	0.03	0.07	-0.05**	0.05*	0.01	0.02	-0.27**	15.7%
	(2.03)	(2.77)	(0.51)	(0.98)	(-2.38)	(1.95)	(0.31)	(0.56)	(-2.30)	

Table 2.3 Cross Section of Corporate Bond Returns: Fama-MacBeth Regression Approach

This table reports the second-stage Fama-MacBeth regressions of excess bond returns in Panel A, abnormal bond returns based on Bessembinder et al. (2009) (BKMX) in Panel B, and excess bond returns after removing small bond issues that are not eligible for inclusion in the Barclays Aggregate Corporate Bond Index in Panel C. All returns are shown in monthly frequency. Bond returns are measured at the firm level by value-weighting individual bonds of the same issuers. The main regressors are the nine cross-sectional variables: asset growth (AG), investment-to-assets (IA), gross profitability (GP), net issuance (NI), book-to-market (BM), momentum (MOM), beta ($BETA$), idiosyncratic volatility ($IVOL$), and accrual ($ACCR$). $log(ME)$ is log-scaled market capitalization. Asset volatility ($AssetVol$) is estimated using past 36-month firm asset returns following Choi (2013). $log(D/A)$ is the log of book debt divided by the sum of market equity and book debt. $Log(BondAmt)$ is the log of value-weighted individual bond amounts outstanding in each firm. $BondAge$ is the time since a bond is issued measured in years. TTM is the value-weighted average of times to maturities of individual bonds for each firm. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. The numbers in parentheses are t-statistics based on the Newey-West standard errors.

Table 2.3 (con't.)

Panel A: Bond Return											
AG	-0.16***										0.01
	(-3.73)										(0.20)
IA		-0.26***									-0.25**
		(-3.41)									(-2.34)
GP			-0.05								0.06
			(-0.97)								(0.95)
NI				-0.05							0.09
				(-0.62)							(0.81)
$ACCR$					-0.13						0.05
					(-0.70)						(0.28)
$SIZE$						-0.02					0.02
						(-0.79)					(0.74)
BM							0.09***				0.05**
							(4.97)				(2.27)
MOM								0.28***			0.27***
								(4.77)			(5.57)
$BETA$									-0.02		-0.02
									(-0.62)		(-0.51)
$IVOL$										0.03**	0.02
										(2.43)	(1.10)
$AssetVol$	0.59**	0.57**	0.52**	0.52**	0.46*	0.36	0.27	0.43*	0.48**	0.08	0.37*
	(2.31)	(2.28)	(2.03)	(1.99)	(1.83)	(1.57)	(1.07)	(1.69)	(2.27)	(0.36)	(1.73)
$log(D/A)$	0.05	0.06	0.04	0.05	0.05	0.02	-0.01	0.08*	0.04	-0.01	0.05*
	(1.14)	(1.24)	(0.89)	(1.11)	(1.10)	(0.72)	(-0.33)	(1.90)	(0.94)	(-0.28)	(1.94)
$log(BondAmt)$	-0.03**	-0.03**	-0.03**	-0.03**	-0.03**	-0.02	-0.03*	-0.04***	-0.03**	-0.03*	-0.04**
	(-2.10)	(-1.98)	(-2.27)	(-2.22)	(-2.18)	(-0.87)	(-1.94)	(-2.65)	(-2.28)	(-1.94)	(-2.04)
$BondAge$	0.01*	0.01*	0.01**	0.01**	0.01**	0.01**	0.01	0.02**	0.01**	0.01**	0.00
	(1.82)	(1.94)	(2.29)	(2.30)	(2.07)	(2.30)	(1.45)	(2.48)	(2.15)	(2.24)	(0.64)
TTM	0.01	0.00	0.01	0.01	0.00	0.00	0.00	0.01*	0.00	0.01*	0.00
	(1.59)	(1.29)	(1.60)	(1.64)	(1.13)	(1.47)	(1.36)	(1.83)	(1.54)	(1.78)	(1.46)
R^2	8.2%	8.8%	8.0%	8.0%	9.0%	8.4%	8.8%	8.4%	8.3%	8.8%	15.2%
$firm\text{-}month\ obs$	298,453	262,949	298,262	298,340	234,351	310,137	256,076	304,967	310,137	310,113	205,794

Table 2.3 (con't.)

Panel B: Abnormal Bond Return Based on BKMX											
AG	-0.15***										-0.02
	(-3.67)										(-0.22)
IA		-0.25***									-0.20*
		(-3.37)									(-1.99)
GP			-0.10**								0.07
			(-2.05)								(1.15)
NI				-0.07							0.07
				(-0.84)							(0.59)
$ACCR$					-0.13						0.05
					(-0.69)						(0.26)
$SIZE$						0.00					0.04**
						(0.25)					(2.16)
BM							0.10***				0.07***
							(5.57)				(3.16)
MOM								0.26***			0.24***
								(4.37)			(4.61)
$BETA$									-0.03		-0.03
									(-0.89)		(-0.74)
$IVOL$										0.03**	0.02
										(2.41)	(1.09)
$AssetVol$	0.31*	0.33*	0.25	0.24	0.23	0.14	0.04	0.13	0.22	-0.14	0.23
	(1.81)	(1.84)	(1.47)	(1.36)	(1.25)	(0.84)	(0.24)	(0.76)	(1.35)	(-0.83)	(1.21)
$log(D/A)$	-0.01	0.00	-0.02	-0.01	-0.01	-0.01	-0.07***	0.02	-0.02	-0.07***	0.02
	(-0.25)	(-0.17)	(-0.79)	(-0.31)	(-0.35)	(-0.46)	(-2.72)	(0.72)	(-0.78)	(-2.85)	(0.79)
$log(BondAmt)$	0.01	0.01	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.01	-0.03
	(0.33)	(0.37)	(0.18)	(0.23)	(0.00)	(-0.03)	(0.49)	(-0.07)	(0.17)	(0.56)	(-1.30)
$BondAge$	0.01**	0.01**	0.01***	0.01***	0.01**	0.01***	0.01*	0.02***	0.01**	0.01***	0.00
	(2.20)	(2.39)	(2.69)	(2.77)	(2.54)	(2.73)	(1.73)	(3.14)	(2.59)	(2.82)	(0.97)
R^2	3.8%	4.1%	3.7%	3.7%	4.2%	3.7%	4.0%	4.0%	3.9%	4.3%	9.74%
$firm\text{-}month\ obs$	298,453	262,949	298,262	298,340	234,351	310,137	256,076	304,967	310,137	310,113	206,120

Table 2.3 (con't.)

Panel C: Bond Return with Barclays Liquidity Constraint Filter											
AG	-0.14***										0.03
	(-3.40)										(0.38)
IA		-0.24***									-0.25**
		(-3.20)									(-2.32)
GP			-0.03								0.04
			(-0.49)								(0.66)
NI				0.00							0.10
				(0.01)							(0.92)
$ACCR$					-0.03						0.24
					(-0.17)						(1.17)
$SIZE$						-0.02					0.01
						(-0.88)					(0.48)
BM							0.09***				0.03
							(4.27)				(1.32)
MOM								0.23***			0.22***
								(3.40)			(4.33)
$BETA$									-0.01		-0.03
									(-0.20)		(-0.80)
$IVOL$										0.05***	0.03*
										(3.09)	(1.70)
$AssetVol$	0.53**	0.51*	0.45*	0.46*	0.48*	0.26	0.21	0.33	0.36*	-0.08	0.32
	(2.00)	(1.96)	(1.67)	(1.70)	(1.85)	(1.10)	(0.79)	(1.24)	(1.65)	(-0.34)	(1.50)
$log(D/A)$	0.06	0.06	0.05	0.06	0.06	0.01	-0.01	0.07	0.04	-0.02	0.05
	(1.14)	(1.17)	(0.96)	(1.10)	(1.20)	(0.51)	(-0.25)	(1.65)	(0.82)	(-0.55)	(1.44)
$log(BondAmt)$	-0.03**	-0.03**	-0.04**	-0.04**	-0.04**	-0.02	-0.03**	-0.04***	-0.04**	-0.03**	-0.04*
	(-2.29)	(-2.16)	(-2.49)	(-2.44)	(-2.51)	(-0.89)	(-2.20)	(-2.88)	(-2.51)	(-2.10)	(-1.87)
$BondAge$	0.01**	0.01**	0.02***	0.02***	0.02**	0.02***	0.01*	0.02***	0.02**	0.02**	0.01
	(2.29)	(2.09)	(2.81)	(2.76)	(2.48)	(2.76)	(1.77)	(3.25)	(2.48)	(2.45)	(0.94)
TTM	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01
	(1.12)	(1.02)	(1.20)	(1.20)	(1.13)	(1.04)	(1.00)	(1.34)	(1.16)	(1.36)	(1.56)
R^2	9.0%	9.5%	8.8%	8.9%	9.8%	9.5%	9.6%	9.3%	9.2%	9.9%	17.0%
$firm\text{-}month\ obs$	226,765	200,396	226,590	226,634	177,451	235,663	194,905	231,838	235,663	235,652	156,297

Table 2.4 Regression of Corporate Bond Returns on Corresponding Equity Returns

This table provides estimation results from the regression of returns on high-minus-low bond portfolios sorted on the nine cross-sectional variables, using the model in (2.4):

$$R^B_{i,t+1} = \alpha + h_1 R^E_{i,t+1} + h_2 R^E_{i,t} + \epsilon_{i,t+1}$$

where R^B_i and R^E_i are the bond and equity excess returns on portfolio i. In the second and third columns of each portfolio, we also include factor returns in the regressions: MKT is the market portfolio return; SMB and HML are the Fama-French small-minus-big and high-minus-low factor returns; UMD is the momentum factor return by Carhart (1997); $TERM$ and DEF are the term and default factor returns constructed following Acharya et al. (2013); CMA and RMW are investment and profitability factors of Fama and French (2015); LIQ is the equity liquidity factor of Pastor and Stambaugh (2003); and $BLIQ$ is the factor mimicking portfolio for corporate bond liquidity constructed by regressing the bond liquidity factor of Lin et al. (2011) on 10 rating by maturity portfolios (long and short maturity portfolios of AAA, AA, A, BBB, and junk-rated bonds). We report the intercept α and the slope coefficients h and b_j for the high-minus-low portfolios. The portfolio sorting variables are asset growth (AG), investment to assets (IA), gross profitability (GP), net issuance (NI), book to market (BM), momentum (MOM), beta ($BETA$), idiosyncratic volatility ($IVOL$), and accrual ($ACCR$). Each end of June, we construct value-weighted decile portfolios for each sorting variable, using information available at the end of the previous years, except for the momentum portfolios. The momentum portfolios are sorted monthly based on six-months ranking and six-months holding periods, following Jegadeesh and Titman (1993). The sample period is from 1979 to 2012. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. The numbers in parentheses are t-statistics based on White (1980) robust standard errors.

Table 2.4 (con't.)

	Asset Growth (AG)			Investment (IA)			Gross Profitability (GP)		
α	-0.15***	-0.13**	-0.12**	-0.14**	-0.20***	-0.18**	0.05	0.00	0.02
	(-2.68)	(-2.27)	(-2.02)	(-2.39)	(-2.93)	(-2.49)	(0.73)	(-0.02)	(0.32)
R^E_{t+1}	0.05***	0.04**	0.04**	0.07***	0.07***	0.07***	0.00	0.01	0.01
	(3.22)	(2.50)	(2.22)	(3.28)	(3.78)	(3.25)	(0.66)	(0.93)	(0.98)
R^E_t	0.02	0.02*	0.02*	0.03	0.03*	0.03*	-0.01	0.00	0.00
	(1.60)	(1.83)	(1.76)	(1.61)	(1.85)	(1.86)	(-0.77)	(-0.34)	(-0.29)
MKT		0.00	0.00		-0.01	-0.01		0.00	-0.01
		(0.12)	(-0.09)		(-0.27)	(-0.63)		(0.07)	(-0.44)
SMB		-0.05***	-0.07***		-0.01	-0.03		-0.03*	-0.04*
		(-2.79)	(-3.09)		(-0.48)	(-1.09)		(-1.77)	(-1.88)
HML		-0.07***	-0.06		-0.04	-0.01		-0.07**	-0.02
		(-2.66)	(-1.47)		(-1.35)	(-0.24)		(-2.37)	(-0.33)
UMD		0.02	0.02*		0.01	0.02		-0.01	0.00
		(1.57)	(1.86)		(0.44)	(1.02)		(-1.02)	(-0.13)
$TERM$		-0.01	-0.01		0.11***	0.11***		0.15***	0.15***
		(-0.28)	(-0.29)		(4.22)	(4.07)		(6.40)	(6.47)
DEF		-0.16**	-0.18**		0.35***	0.33***		0.27**	0.25**
		(-2.26)	(-2.45)		(3.51)	(3.22)		(2.48)	(2.18)
CMA			-0.02			-0.06			-0.12***
			(-0.32)			(-1.20)			(-2.62)
RMW			-0.04			-0.05			-0.03
			(-1.26)			(-1.45)			(-0.97)
LIQ			-0.00*			0.00			-0.00***
			(-1.78)			(-0.06)			(-3.50)
$BLIQ$			0.20			0.30			0.45
			(0.78)			(0.86)			(1.50)
R^2	6.1%	17.5%	18.3%	9.7%	22.6%	23.6%	0.7%	20.0%	22.4%

Table 2.4 (con't.)

	Net Issuance (NI)			Book-to-Market (BM)			Momentum (MOM)		
α	-0.05	-0.10*	-0.05	0.03	0.03	0.03	0.19**	0.20*	0.22**
	(-0.97)	(-1.96)	(-0.96)	(0.53)	(0.59)	(0.46)	(2.04)	(1.83)	(2.14)
R^E_{t+1}	0.03	0.02	0.01	0.06***	0.03**	0.03**	0.13***	0.20***	0.19***
	(1.22)	(0.87)	(0.61)	(4.20)	(2.33)	(2.33)	(5.26)	(5.04)	(5.19)
R^E_t	0.00	0.00	0.00	0.03**	0.02*	0.02*	0.02	0.03	0.02
	(0.49)	(-0.23)	(-0.39)	(2.37)	(1.70)	(1.66)	(0.94)	(1.53)	(1.39)
MKT		0.06***	0.05***		0.02	0.02		-0.02	-0.01
		(4.21)	(4.09)		(1.26)	(1.27)		(-0.60)	(-0.47)
SMB		0.02*	0.01		0.05***	0.06**		-0.04	0.02
		(1.78)	(0.35)		(2.64)	(2.51)		(-1.28)	(0.44)
HML		0.01	0.06**		0.09***	0.09**		0.03	0.06
		(0.72)	(2.30)		(3.17)	(2.38)		(0.83)	(1.02)
UMD		0.00	0.00		-0.02	-0.02		-0.13**	-0.14**
		(-0.46)	(0.21)		(-1.39)	(-1.42)		(-2.04)	(-2.45)
$TERM$		-0.03*	-0.03**		-0.07***	-0.07***		0.05*	0.05
		(-1.75)	(-1.98)		(-2.87)	(-2.83)		(1.67)	(1.61)
DEF		0.21***	0.20***		0.22***	0.23***		0.12	0.23*
		(3.31)	(3.28)		(2.96)	(3.03)		(1.07)	(1.89)
CMA			-0.08***			0.00			-0.06
			(-2.67)			(-0.06)			(-0.78)
RMW			-0.09***			0.02			0.10*
			(-4.03)			(0.47)			(1.77)
LIQ			0.00			0.00***			-0.00***
			(1.27)			(4.20)			(-3.83)
$BLIQ$			-0.13			-0.09			-1.73***
			(-0.63)			(-0.30)			(-3.09)
R^2	3.6%	32.3%	35.5%	10.8%	33.7%	33.9%	21.0%	26.4%	31.0%

Table 2.4 (con't.)

	Beta ($BETA$)			Idio. Vol ($IVOL$)			Accrual ($ACCR$)		
α	-0.03	-0.01	0.00	0.12	0.12	0.11	0.07	0.07	0.06
	(-0.44)	(-0.10)	(0.00)	(1.31)	(1.15)	(1.17)	(1.26)	(1.29)	(1.03)
R^E_{t+1}	0.05***	0.03*	0.02	0.03	0.01	0.01	0.13***	0.12***	0.12***
	(3.13)	(1.77)	(1.44)	(1.56)	(1.06)	(0.79)	(6.31)	(6.34)	(5.80)
R^E_t	-0.01	-0.02	-0.02	0.00	-0.01	-0.01	0.03*	0.02*	0.02*
	(-0.36)	(-0.99)	(-1.04)	(0.13)	(-0.82)	(-0.89)	(1.91)	(1.92)	(1.78)
MKT		0.09***	0.09***		0.11***	0.11***		-0.03*	-0.03*
		(3.32)	(3.72)		(3.75)	(4.07)		(-1.97)	(-1.78)
SMB		0.08***	0.02		0.15***	0.08**		0.04*	0.05*
		(3.16)	(0.53)		(4.86)	(2.18)		(1.97)	(1.93)
HML		0.04	0.02		0.05	0.02		0.01	0.00
		(1.10)	(0.46)		(1.17)	(0.33)		(0.40)	(0.02)
UMD		-0.01	0.00		-0.02	0.00		0.02	0.02
		(-0.45)	(0.16)		(-0.57)	(-0.03)		(1.53)	(1.23)
$TERM$		-0.22***	-0.22***		-0.20***	-0.20***		0.00	0.00
		(-7.80)	(-8.04)		(-6.65)	(-6.70)		(-0.08)	(-0.03)
DEF		-0.17	-0.25*		-0.05	-0.15		-0.14**	-0.14**
		(-1.33)	(-1.89)		(-0.35)	(-1.18)		(-2.15)	(-1.99)
CMA			0.05			0.08			0.01
			(0.90)			(0.99)			(0.25)
RMW			-0.14***			-0.13***			0.02
			(-3.35)			(-3.13)			(0.78)
LIQ			0.00***			0.00			-0.00**
			(2.71)			(0.39)			(-2.07)
$BLIQ$			1.16***			1.69***			-0.03
			(2.82)			(3.69)			(-0.11)
R^2	7.9%	34.5%	39.9%	6.4%	34.9%	41.0%	25.1%	32.0%	32.1%

Table 2.5 The Cross Section of Corporate Bond Returns That Are Hedged Against Equity Risk

This table provides average returns on corporate bond returns that are hedged against the equity risk of the same issuing firms for low (L), high (H), and high-minus-low (HL) decile portfolios sorted on the nine anomaly variables. We also report average portfolio characteristics (leverage and asset volatility) and alphas from the time-series regressions the hedged bond portfolio returns on 10 factor returns considered in Table 2.4. The anomaly variables are asset growth AG (Panel A), investment-to-assets IA (Panel B), gross profitability GP (Panel C), net issuance NI (Panel D), book-to-market (BM) (Panel E), momentum (MOM) (Panel F), beta ($BETA$) (Panel G), idiosyncratic volatility ($IVOL$) (Panel H), and accrual ($ACCR$) (Panel I). *Leverage* is measured as total book debt to total book debt plus the market value of equity and *Asset Vol* is the monthly standard deviation measured using firm asset returns from the past 36 months. h is hedge ratios estimated from the Merton model as explained in Section 2.4.3.1. The bond returns hedged against equity risk, $R^B - hR^E$, is defined as the difference between excess returns on the bond portfolio and the product of hedge ratios and excess equity returns on the portfolio of the same firms. The equal-weighted (EW) and value-weighted (VW) decile portfolios are sorted at the end of each June using the anomaly variables available at the end of the previous years, except for the momentum portfolios. The momentum portfolios are sorted monthly based on six-month ranking and six-month holding periods, following Jegadeesh and Titman (1993). Monthly equal-weighted bond returns are measured by equally weighting firm-level bond returns, where the firm-level bond returns are value-weighted individual bond returns. The sample period is from 1979 through 2012. *, **, and *** for the HL portfolios denote statistical significance at the 10%, 5%, and 1% levels, respectively. The numbers in parentheses are t-statistics based on White (1980) robust standard errors.

Table 2.5 (con't.)

Panel A: Sorting on Asset Growth (AG)					
	Portfolio Statistics			Hedged Bond Return ($R^B - hR^E$)	
EW	L	H		HL	
				Average	α
Leverage	0.49	0.43	$R^B - hR^E$	-0.29***	-0.22***
Asset Vol	0.26	0.27		(-4.90)	(-3.46)
h	0.02	0.02			
VW					
Leverage	0.47	0.45	$R^B - hR^E$	-0.17***	-0.12**
Asset Vol	0.22	0.23		(-3.25)	(-2.16)
h	0.01	0.01			
Panel B: Sorting on Investment (IA)					
EW	L	H		HL	
				Average	α
Leverage	0.45	0.42	$R^B - hR^E$	-0.20***	-0.13**
Asset Vol	0.25	0.28		(-3.55)	(-2.02)
h	0.02	0.02			
VW					
Leverage	0.46	0.34	$R^B - hR^E$	-0.17***	-0.17**
Asset Vol	0.21	0.25		(-2.75)	(-2.20)
h	0.01	0.01			
Panel C: Sorting on Gross Profitability (GP)					
EW	L	H		HL	
				Average	α
Leverage	0.56	0.27	$R^B - hR^E$	-0.05	-0.04
Asset Vol	0.19	0.27		(-1.04)	(-0.72)
h	0.02	0.02			
VW					
Leverage	0.72	0.14	$R^B - hR^E$	0.07	0.04
Asset Vol	0.14	0.23		(1.14)	(0.60)
h	0.01	0.00			

Table 2.5 (con't.)

Panel D: Sorting on Net Issuance (NI)					
	Portfolio Statistics			Hedged Bond Return ($R^B - hR^E$)	
EW	L	H		HL	
				Average	α
Leverage	0.39	0.49	$R^B - hR^E$	-0.02	0.02
Asset Vol	0.21	0.24		(-0.51)	(0.41)
h	0.01	0.02			
VW					
Leverage	0.43	0.54	$R^B - hR^E$	-0.04	-0.04
Asset Vol	0.19	0.19		(-0.93)	(-0.76)
h	0.01	0.01			
Panel E: Sorting on Book-to-Market (BM)					
EW	L	H		HL	
				Average	α
Leverage	0.25	0.60	$R^B - hR^E$	0.17**	0.00
Asset Vol	0.29	0.20		(2.39)	(0.04)
h	0.02	0.02			
VW					
Leverage	0.16	0.64	$R^B - hR^E$	0.08	0.05
Asset Vol	0.23	0.17		(1.28)	(0.74)
h	0.00	0.02			
Panel F: Sorting on Momentum (MOM)					
EW	L	H		HL	
				Average	α
Leverage	0.57	0.39	$R^B - hR^E$	0.35***	0.31***
Asset Vol	0.29	0.27		(3.69)	(3.57)
h	0.02	0.02			
VW					
Leverage	0.56	0.41	$R^B - hR^E$	0.31***	0.25**
Asset Vol	0.26	0.25		(3.09)	(2.23)
h	0.02	0.01			

Table 2.5 (con't.)

Panel G: Sorting on Beta ($BETA$)					
	Portfolio Statistics			Hedged Bond Return ($R^B - hR^E$)	
EW	L	H		HL	
				Average	α
Leverage	0.45	0.49	$R^B - hR^E$	0.06	0.12**
Asset Vol	0.16	0.34		(0.66)	(2.28)
h	0.01	0.03			
VW					
Leverage	0.40	0.62	$R^B - hR^E$	-0.06	-0.02
Asset Vol	0.14	0.30		(-0.76)	(-0.23)
h	0.00	0.02			
Panel H: Sorting on Idio. Vol ($IVOL$)					
EW	L	H		HL	
				Average	α
Leverage	0.39	0.54	$R^B - hR^E$	0.17	0.18**
Asset Vol	0.15	0.30		(1.65)	(2.46)
h	0.01	0.03			
VW					
Leverage	0.36	0.53	$R^B - hR^E$	0.09	0.06
Asset Vol	0.16	0.30		(0.99)	(0.65)
h	0.00	0.02			
Panel I: Sorting on Accrual ($ACCR$)					
EW	L	H		HL	
				Average	α
Leverage	0.39	0.38	$R^B - hR^E$	-0.04	-0.09*
Asset Vol	0.29	0.27		(-0.85)	(-1.67)
h	0.02	0.02			
VW					
Leverage	0.29	0.27	$R^B - hR^E$	0.06	0.02
Asset Vol	0.26	0.26		(1.08)	(0.25)
h	0.01	0.01			

Table 2.6 Fama-MacBeth Regression of Hedged Bond Returns

This table provides second-stage regressions of the extended Fama-MacBeth regression in (2.6):

$$\lambda_t = \alpha + \beta S_t + \gamma Z_t + \epsilon_{i,t}$$

where λ_t is the first-stage regression coefficient on each anomaly variable $X_{i,t}$, estimated from the following monthly cross-sectional regressions where the dependent variable is the corporate bond returns hedged against equity risk, $R^B_{i,t+1} - h_{i,t}R^E_{i,t+1}$:

$$R^B_{i,t+1} - h_{i,t}R^E_{i,t+1} = a_t + \lambda_t X_{i,t} + \text{ctrls}_{i,t} + e_{i,t+1}$$

The hedge ratio h_t is estimated from the Merton model. S_t is the sentiment index in Baker and Wurgler (2006). As control variables in the second-stage regression (2.6), we include market risk premium predictors such as dividend yield (DY), term spread (TS), default spread (DS), and T-bill rate (TB), as well as the log VIX (VX). We use the old VIX series for the sample period in which the VIX is not available. The sample period is from 1986 through 2010 based on the availability of the volatility and sentiment indices. The reported t-statistics in parentheses are based on the Newey-West standard errors.

Table 2.6 (con't.)

	Asset Growth (AG)		Investment (IA)		Gross Profitability (GP)	
Const	-0.13***	-0.15***	-0.23***	-0.24***	-0.07	0.00
	(-2.94)	(-4.13)	(-3.06)	(-3.00)	(-1.36)	(-0.04)
S_t	-0.11*	-0.12**	-0.25***	-0.29***	0.13**	0.17
	(-1.79)	(-2.54)	(-2.62)	(-2.97)	(2.26)	(1.60)
DY		-0.03		-0.02		-0.24**
		(-0.34)		(-0.11)		(-2.01)
TS		-0.11		-0.26*		0.13
		(-1.52)		(-1.70)		(1.32)
DS		0.15**		0.20		0.34**
		(2.28)		(1.25)		(2.33)
TB		0.04		-0.06		0.19
		(0.44)		(-0.28)		(1.38)
VX		-0.08		-0.12		-0.17**
		(-1.49)		(-1.03)		(-2.41)
R^2	1.8%	7.7%	2.9%	6.5%	1.7%	7.1%

	Net Issuance (NI)		Book-to-Market (BM)		Momentum (MOM)	
Const	-0.03	0.01	0.10***	0.09***	0.29***	0.29***
	(-0.36)	(0.12)	(5.01)	(4.81)	(5.50)	(5.57)
S_t	-0.23**	-0.22**	0.06**	0.07***	0.04	-0.01
	(-2.26)	(-1.96)	(2.44)	(2.59)	(0.64)	(-0.11)
DY		0.11		-0.07*		-0.08
		(0.50)		(-1.69)		(-0.65)
TS		-0.14		0.07**		0.06
		(-0.74)		(1.97)		(0.65)
DS		0.05		0.05		-0.14
		(0.22)		(0.95)		(-1.33)
TB		-0.11		0.07		0.25
		(-0.37)		(1.41)		(1.51)
VX		-0.16		-0.04		0.25
		(-1.21)		(-1.19)		(1.51)
R^2	1.7%	4.0%	2.3%	5.9%	0.1%	3.7%

Table 2.6 (con't.)

	Beta ($BETA$)		Idio. Vol ($IVOL$)		Accrual ($ACCR$)	
Const	-0.03	-0.04	0.04***	0.05***	-0.10	-0.12
	(-0.75)	(-0.89)	(2.80)	(2.86)	(-0.52)	(-0.55)
S_t	-0.11**	-0.13**	-0.04**	-0.03	-0.02	0.00
	(-2.42)	(-2.17)	(-2.47)	(-1.41)	(-0.11)	(-0.01)
DY		-0.09		-0.09***		-0.11
		(-1.12)		(-2.76)		(-0.24)
TS		0.10		0.09***		0.23
		(1.45)		(2.92)		(0.54)
DS		0.14		0.11***		0.12
		(1.32)		(3.30)		(0.26)
TB		0.03		0.09**		0.11
		(0.32)		(1.97)		(0.19)
VX		-0.22***		-0.09***		-0.14
		(-3.82)		(-4.00)		(-0.48)
R^2	2.6%	10.4%	1.7%	9.0%	0.0%	0.2%

Table 2.7 Predictive Regression of Equity-Hedged Bond Returns: Long and Short Portfolio Approach

This table provides the estimation of the following regression for the long and short legs of long-short portfolios sorted on the nine anomaly variables:

$$R^B_{i,t+1} - h_{i,t}R^E_{i,t+1} = a_0 + a_1 S_t + a_2 Z_t + e_{i,t+1}$$

where $R^B_{i,t+1} - h_{i,t}R^E_{i,t+1}$ is the difference between bond excess returns on portfolios $R^B_{i,t+1}$ and the product of hedge ratios $h_{i,t}$ and equity excess returns on the portfolios of the same firms $R^E_{i,t+1}$; S_t is the sentiment index of Baker and Wurgler (2006). The hedge ratio $h_{i,t}$ is estimated from the Merton model. As additional control variables (Z_t), we include market risk premium predictors such as dividend yield (DY), term spread (TS), default spread (DS), and the T-bill rate (TB), as well as the log VIX (VX), all measured at time t. To save space, we report only the coefficients on S_t and Z_t. The anomaly variables are asset growth (AG), investment-to-assets (IA), gross profitability (GP), net issuance (NI), book-to-market (BM), momentum (MOM), beta ($BETA$), idiosyncratic volatility ($IVOL$), and accrual ($ACCR$). We form value-weighted decile portfolios sorted at the end of each June using the anomaly variables that are available at the ends of the previous years, except for the momentum portfolios. The momentum portfolios are sorted monthly based on six-months ranking and six-months holding periods, following Jegadeesh and Titman (1993). The sample period is from 1986 through 2010 based on the availability of the volatility and sentiment indices. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. The numbers in parentheses are t-statistics based on White (1980) robust standard errors.

Table 2.7 (con't.)

	Asset Growth (AG)		Investment (IA)		Gross Profitability (GP)	
	Long	Short	Long	Short	Long	Short
Const	0.63***	0.39***	0.58***	0.47***	0.38***	0.29***
	(7.31)	(5.02)	(6.78)	(5.34)	(4.93)	(4.39)
S_t	-0.09	-0.29***	-0.08	-0.31***	-0.01	-0.05
	(-0.83)	(-2.66)	(-0.80)	(-2.60)	(-0.09)	(-0.56)
DY	-0.01	0.07	-0.16	0.07	0.12	-0.17
	(-0.05)	(0.41)	(-1.01)	(0.39)	(0.70)	(-1.26)
TS	0.26*	0.04	0.34**	0.04	0.17	0.34***
	(1.79)	(0.28)	(2.25)	(0.27)	(1.03)	(3.06)
DS	0.30	0.43***	0.50***	0.64***	0.13	0.24
	(1.59)	(3.43)	(2.76)	(4.22)	(0.79)	(1.53)
TB	-0.15	-0.10	0.00	-0.12	-0.05	0.21
	(-0.82)	(-0.51)	(0.02)	(-0.58)	(-0.26)	(1.27)
VX	0.12	0.05	0.13	0.00	0.00	-0.16*
	(1.04)	(0.46)	(1.09)	(0.02)	(0.00)	(-1.80)
R^2	1.3%	1.8%	1.2%	1.6%	2.2%	2.4%

	Net Issuance (NI)		Book-to-Market (BM)		Momentum (MOM)	
	Long	Short	Long	Short	Long	Short
Const	0.45***	0.42***	0.60***	0.36***	0.62***	0.14
	(6.05)	(5.27)	(6.65)	(4.89)	(7.74)	(1.12)
S_t	-0.04	-0.16*	-0.05	-0.22**	0.00	-0.59**
	(-0.47)	(-1.70)	(-0.39)	(-2.05)	(-0.03)	(-2.58)
DY	-0.23	0.17	0.11	-0.07	0.20	0.01
	(-1.52)	(0.99)	(0.60)	(-0.48)	(1.17)	(0.04)
TS	0.42***	0.02	0.10	0.21	0.07	0.33
	(3.05)	(0.10)	(0.57)	(1.64)	(0.47)	(1.15)
DS	0.39***	0.28	0.43**	0.23*	-0.08	0.31
	(2.89)	(1.49)	(2.05)	(1.69)	(-0.48)	(1.17)
TB	0.35*	-0.21	-0.27	0.09	-0.32	0.10
	(1.76)	(-1.01)	(-1.26)	(0.53)	(-1.57)	(0.29)
VX	0.02	0.16	-0.01	-0.03	0.21**	-0.25
	(0.17)	(1.41)	(-0.09)	(-0.27)	(2.03)	(-1.44)
R^2	3.3%	1.0%	0.5%	6.0%	0.5%	6.8%

Table 2.7 (con't.)

	Beta ($BETA$)		Idio. Vol ($IVOL$)		Accrual ($ACCR$)	
	Long	Short	Long	Short	Long	Short
Const	0.48***	0.45***	0.41***	0.54***	0.51***	0.49***
	(6.53)	(5.50)	(5.46)	(6.10)	(5.40)	(5.75)
S_t	0.01	-0.31***	0.01	-0.12	-0.33**	-0.17
	(0.15)	(-2.73)	(0.13)	(-0.77)	(-2.48)	(-1.53)
DY	-0.09	0.24	-0.23	-0.07	0.11	0.06
	(-0.53)	(1.31)	(-1.36)	(-0.28)	(0.54)	(0.34)
TS	0.40***	0.00	0.49***	0.38*	0.04	0.03
	(2.89)	(0.01)	(3.37)	(1.88)	(0.23)	(0.17)
DS	0.25*	-0.12	0.26*	0.13	0.40**	0.47***
	(1.76)	(-0.66)	(1.71)	(0.64)	(2.28)	(3.10)
TB	0.25	-0.32	0.40**	0.17	-0.30	-0.10
	(1.28)	(-1.37)	(2.00)	(0.62)	(-1.29)	(-0.46)
VX	0.01	0.14	-0.03	-0.10	0.13	-0.05
	(0.12)	(1.26)	(-0.25)	(-0.78)	(1.05)	(-0.40)
R^2	3.0%	5.1%	3.7%	2.4%	2.0%	2.8%

CHAPTER 3

LABOR SKILLS AND TECHNOLOGY CHANGE

3.1 Introduction

Investment-specific technology shock has known to be an important factor in explaining aggregate productivity and economic growth (Greenwood et al. (1997, 2000), Fisher (2006)). Since positive investment-specific technology shock is associated with relative decline in investment costs, Papanikolaou (2011) and Kogan and Papanikolaou (2013, 2014) show that technology shock is a priced risk factor that explain time-series and cross-sectional return predictability in asset prices.

The advance in technology is also associated with the demand of labor forces. Technology change has been skill-biased in that the productivity of skilled workers has increased more rapidly than that of less skilled workers. Much attention has given to the technological change due to its ability to explain several phenomena in labor market, such as increasing skill premium, rising inequality, and job polarization (Krusell et al. (2000), Acemoglu (2002), Parker and Vissing-Jorgensen (2010), Autor and Dorn (2013)).

In this paper, I examine the role of technology shock on firm behavior and asset prices through the labor channel. Based on the labor economics literature, I postulate that the firm production depends on two labor groups (skilled and unskilled workers) and two aggregate shocks (productivity and technology shocks). In this setup, technology innovation involves changes in the productivity of skilled labor. If firms are operated only by skilled workers, those firms will be totally exposed to technology shock. On the other hand, firms will be totally isolated from the technology change if they are operated by unskilled workers. This simple relation between technology shock and labor skill composition raises rich implications both for corporate behavior and asset prices.

Using the quality-adjusted price of capital goods relative to consumption goods proposed by Greenwood et al. (1997) as proxy for technology innovation, I conduct empirical tests to investigate the dynamic firm behavior in response of technology shock. I find that high skill firms tend to have higher profitability, and increase capital expenditures when positive shock arrives, compared to low skill firms. The increase in capital investment is an intuitive outcome from the fact that capital and skilled labor are complements in the production function.[1]

[1] In order to develop testable hypotheses, I assume the firm production with two labor groups, while abstracting capital input. However, it is not possible to identify the number of skilled workers in each firm due to limitation of data. For this reason, I provide an indirect evidence of capital investment through capital-skill complementarity logic.

Having identified the response of firms alongside the technology change, I then investigate asset pricing implications. The previous results imply that high skill firms are more sensitive to technology shock. Therefore, if technology shock carries a negative risk premia as in Papanikolaou (2011), high skill firms should have lower expected returns than low skill firms.

Regarding the price of technology risk, Papanikolaou (2011) and Kogan and Papanikolaou (2013, 2014) argue that a negative risk price is needed to explain the cross-sectional return predictability. However, Li (2014) and Garlappi and Song (2016) propose a positive risk price of technology shock. Due to the debate in the literature, I conduct cross-sectional tests to find the sign of risk price. First, I calculate individual stock's technology beta and find that firms with higher technology beta have higher returns. I also implement Fama-MacBeth regressions with a broad set of test portfolios to directly infer the price of risk. Consistent with portfolio sorts, my estimation results indicate positive technology risk premia.

Turning to the firm-level asset pricing tests, I find that high skill firms have higher returns, using portfolios sorts and Fama-MacBeth regressions. More importantly, I find that almost half of the skill premia can be subsumed by technology factor. For example, the return spread measured by Fama-French five factor model is 0.75% monthly. However, it becomes to 0.47% when technology factor is included to obtain alphas, implying that approximately 40% of return spread can be explained by technology factor alone. The results provide empirical supports for the hypothesis that high skill firms have higher exposure to technology innovation.

My work mostly contributes to recent advances in asset pricing with labor market. Among the growing interest on the importance of labor market, only few papers highlight the importance of labor skills. A closely related paper is Ochoa (2015), which shows that high skill firm are risky due to their exposure to volatility shock. Since skilled labor is costly to adjust, investors demand high returns for high skill firms, especially in highly volatile states. Another work is Belo et al. (2016). The paper focuses on the negative hiring-return relation in the cross-section and find that the relation is steeper for high skill firms, consistent with the prediction from investment-based model. Both papers exploit the costly adjustment nature of high skill firms. My findings highlight the importance of economic-wide risk factor to firm behavior and asset prices, without characterizing frictions in the framework.

I also contribute to the literature that study the effect of technology change on asset prices. Christiano and Fisher (2003) first relates technology shock to equity premium at aggregate level. Papanikolaou (2011) and Kogan and Papanikolaou (2013, 2014) further document that technology shock drives cross-sectional heterogeneity in asset prices, by linking risk exposure to various firm-level characteristics. The key finding is that technology shock carries a negative risk premia. On the other hand, Li (2014) suggest a unified framework that explain the value and momentum strategies simultaneously. The paper argues that positive risk premia of technology shock is essential to explain the phenomenon. Garlappi and Song (2016) examine the risk price of technology shock through the value and momentum strategies to find a positive risk premia of the shock. The findings in this paper suggest the positive price of technology risk, thereby contributing to the debate.

The rest of the paper is organized as follows. Section 3.2 develops the main hypotheses throughout this paper. data sources. Section 3.3 describes data sources and definitions of main variables. Section 3.4 presents empirical results. Section 3.5 concludes.

3.2 Hypothesis Development

I develop main testable hypotheses based on the labor economics literature. Consider a production technology similar to Autor et al. (2008) where each firm produces a perishable good with two inputs, skilled labor (L^s) and unskilled labor (L^u),

$$Y_{i,t} = A_t\big[\alpha_i(Z_t L^s_{i,t})^\rho + (1-\alpha_i)(L^u_{i,t})^\rho\big]^{\frac{1}{\rho}}. \tag{3.1}$$

For convenience, firms are labeled by skill index i with assumption,

$$\alpha_i > \alpha_j, \text{ if } i > j. \tag{3.2}$$

α_i represents the skill intensity (share of work activities allocated to skilled labor) of firm i. In this setting, heterogeneity across firms stems from skill intensity parameter, α. For example, if α equals to one, firm operation depends only on skilled workers and hence will be perfectly exposed to the advances in technology. In contrast, firm will be totally isolated from the shock when α equals to zero. Since the exposure to technology shock is closely tied to skilled labor dependency, skill-intensive firms should have profits that are more sensitive to the shock. On the other hand, the effect of productivity shock is same regardless of firm labor mix. Thus, I reach the first testable hypothesis:

Hypothesis 1: Firms that require more skilled labor have profits that are more sensitive to the technology shock, compared to low skill firms.

The increase in skilled labor productivity gives an incentive to firms to hire more skilled workers. If wage is sticky enough, positive technology shock should correspond to an increase in the number of skilled workers, and more so for firms that require high-level of labor skills. However, it is not possible to identify changes in workforce details within a firm from the public available data, such as Compustat. Instead, I look at whether firm capital expenditure increases with technology shock. The logic behind is the physical capital-skill (skilled labor) complementarity first suggested in Griliches (1969).[2] I apply this logic into firm-level analysis and hypothesize the following:

Hypothesis 2: Skill-intensive firms increase capital expenditure more than low skill firms, in response of positive technology innovation.

[2] Moreover, Acemoglu (1998) and Krusell et al. (2000) combine capital-skill complementarity and technology change to address inequality issues in the economy.

I argue that firm's exposure to technology shock is determined by its usage of skilled labor. If technology innovation systematically affects firm operation, the shock should be regarded as economic-wide risk that carry a risk premia. As such, it is important to examine asset pricing implication of labor skills. If technology shock is a risk that carry a negative risk premia as in Papanikolaou (2011), high skill firms should have lower expected stock returns. In contrast, those firms should have higher returns if technology shock is associated with positive risk premia as in Li (2014) and Garlappi and Song (2016). This lead to the last testable hypothesis:

Hypothesis 3: If technology shock carries positive (negative) risk premia, then high skill firms have higher (lower) expected stock returns.

In the following section, I describe data and variables used in empirical tests.

3.3 Data

3.3.1 Measure of Labor Skill

The key variable throughout the paper is the labor skill of a firm. Since it is not able to obtain workforce details within a firm, I define labor skill measure at industry level each year as the fraction of high skilled workers. I first classify skilled labor at occupation level using the Dictionary of Occupational Titles (DOT): Revised Fourth Edition, 1991 from U.S. Department of Labor. DOT includes the information on Specific Vocational Preparation (SVP), which measures the amount of lapsed time required by a typical worker to learn the techniques, acquire the information, and develop the facility needed for average performance in a specific job-worker situation. The value of SVP ranges from 1 to 9, where SVP =1 corresponds to the lowest preparation, and SVP = 9 corresponds to the highest preparation of over 10 years. I define a high skill occupation if its SVP index is equal to or greater than 7 (this corresponds to an occupation that requires over 2 years of preparation), and low skill otherwise.

I then obtain industry level measure of labor skill by calculating the percentage of skilled workers in the industry. The data on the number of workers by occupation in each industry is from the Bureau of Labor Statistics, Occupational Employment Statistics (OES) program.[3] I map SVP information of each occupation to OES data to obtain the skill intensity across industries.[4]

In Table 3.1, I report top 5 and bottom 5 skill industries in 2001. In high skill industries, over half of employees are skilled workers while bottom industries use approximately one percent of skilled workers among total number of employees. It is clear that different industries require different level of labor skill.

[3] Before 1996, the OES provides employment data once in three years. Therefore, I use the same industry data for three consecutive years to ensure continuous coverage of the full set of industries in early years.

[4] From 1991 to 2001, I calculate industry skill at 3-digit SIC level and 4-digit NAICS level onwards.

3.3.2 Measure of Technology Shock

In the empirical analysis, I rely on two measures of technology shocks. The first measure is the price of new equipment relative to consumption proposed by Greenwood et al. (1997, 2000), which is obtained from macroeconomic data. Krusell et al. (2000) interpret this measure as skill-biased technological change and find that it explains most of variation in skill premium. Following Garlappi and Song (2016), I proxy the technology shock as the innovation in quality-adjusted equipment price relative to consumption:

$$Tech_t = -(ln(P_I/P_C)_t - ln(P_I/P_C)_{t-1}), \tag{3.3}$$

P_I denotes the price of equipment, and P_C is the price deflator for nondurable consumption goods from the National Income and Product Accounts (NIPA) tables.[5]

The second measure of technology shock is from Papanikolaou (2011), which is obtained from financial data. It is the stock return spread between investment and consumption good producers,

$$IMC_t = r_t^I - r_t^C. \tag{3.4}$$

For the classification between investment and consumption producers, I follow Gomes et al. (2009) which classify industries into investment and consumption sectors based on the contribution to the final demand category in National Income and Product Accounts (NIPA).

This specification assumes that firms producing investment goods have different loadings on the technology shock compared to consumption producers, while both firms have same loadings on the productivity shock. The return difference between investment and consumption firms can be an appropriate measure for technology shock, neutralizing the effect of productivity shock. The advantage of this measure is that it can be measured at monthly or even higher frequency, where the price series in (3.3) is calculated on annual basis.

3.4 Empirical Findings

3.4.1 Sample & Summary Statistics

I construct sample from the intersection of CRSP and Compustat database that span from 1991 to 2012. I exclude financial and utility firms due to their regulatory environment. To avoid results driven by microcap firms discussed in Fama and French (2008b), I exclude firms in the lowest 20th size quantile for each year. I keep track of following variables. *Size* is the firm market capitalization; *BM* is the book-to-market ratio; *Inv* is the capital expenditures (Compustat item CAPX) to assets ratio; *Book. Lev* is the total debt (item DLC+DLTT) divided by sum of debt and

[5] I thank Ryan Israelsen for sharing the quality-adjusted equipment price series used in Israelsen (2010).

market capitalization; $Profit$ is the gross profits (item REVT-COGS) to assets as in Novy-Marx (2013); $Cash\ Flow$ is the ratio of income before extraordinary items (item IB) plus depreciation (item DP) to total assets; $Labor\ Share$ is the number of employees (item EMP) to assets ratio; $Cash$ is the ratio of cash and cash equivalents (item CHE) to assets ratio.

In Table 3.2, I report the time-series average of median characteristics for quintile skill portfolios. On average, high skill firms tend to be smaller, and have lower book-to-market ratio than low skill firms. Moreover, high skill firms have low level of financial leverage, while holding more cash. To summarize, labor skill intensity is related to several firm-level characteristics in the cross-section.

The key property of skill composition is that high skill firms have high exposure to the technology shock. As a preliminary investigation, I directly estimate each stock's technology beta using IMC return as a proxy for technology shock. A stock's monthly IMC beta is obtained by regressing stock return on the IMC return (defined in equation (3.4)):

$$r_{i,t} = a_{i,t} + \beta_{i,t}^{IMC} + \epsilon_{i,t}, \forall i, t. \tag{3.5}$$

I use 36 month rolling window and require stocks to have at least 24 observation in the window. β^{IMC1} is stock's IMC beta obtained from (3.5) and β^{IMC2} is obtained by adding market risk factor to (3.5). As reported in 3.2, high skill firms show higher sensitivity to the technology shock than low skill firms. The median IMC beta of high skill portfolio is 1.02 on average where the median beta of low skill portfolio is 0.551. I find a similar increasing pattern for β^{IMC2}. The results clearly show that high skill firms are more exposed to the technology change.

3.4.2 Response to Technology Shock

I investigate how firms react in response to the technology shock. To test my first hypothesis, I consider a specification of the form:

$$Profit_{i,j,t+1} = \beta * Skill_{i,j,t} + \gamma * Shock_{t+1} + \delta(Skill_{i,j,t} * Shock_{t+1}) + ctrls_{i,j,t} + \epsilon_{i,j,t+1}. \tag{3.6}$$

I first regress logarithm of firm profit at year t+1 on lagged skill, technology shock, and skill-shock interaction variable. I also include several controls such as firm fixed effects, year fixed effects, industry-year fixed effects (2 digit SIC level), logarithm of firm assets, Tobin's Q, tangibility, book leverage, capital investment, firm cash holding, and firm age. The standard errors are clustered at the firm and year level.

In Table 3.3, I report the estimation results. In column (1) where technology shock ($Tech$) is the variable of interest, a one-standard-deviation increase in technology shock (1.8) corresponds to 0.9% increase in profits on average. Moreover, I find that high skill firms tend to have higher profits, when positive technology shock arrives. In column (2), $Tech * Skill$ is estimated as 0.014 at 1% significance level. This implies that given a typical increase in the technology shock, a one-standard-deviation increase in skill (0.14) leads to a 0.2% more increase in profitability. In column (3) to (4), I further control for productivity shock (TFP) in the specification to examine the robustness of results.[6] I find that firm profit is mostly related to the technology shock, not to the productivity shock. Overall, the results suggest that the volatility of firm profits increases as firm use more skilled labor.

If productivity of high skill workers depends on the technology innovation, it is natural to ask whether firms tend to hire more skilled labor when positive technology shock arrives. However, from the publicly available data such as Compustat, it is not possible to identify labor composition details (e.g. number of employees at occupation level) within a firm. Due to data limitation, I exploit alternative link between labor skills and firm behavior. In the literature, physical capital and skilled labor have been argued as complementary inputs in the production function. This implies that an increase in skilled labor should correspond to an increase in capital. Based on this logic, I indirectly examine firm capital expenditure instead of skilled labor to test the second hypothesis.

In Table 3.4, I present the estimation results. The empirical design is similar to (3.6) except for control variables used. In the specification, I include Tobin's Q, logarithm of assets, asset tangibility, book leverage, cash holdings, and cash flow as controls. In column (1), a one-standard-deviation increase in technology shock is associated with approximately 3% increase in investment on average. I also find that high skill firms increase capital expenditure more than low skill firms, when positive shock arrives. Given a typical increase in the technology innovation, a one-standard-deviation increase in skill yields a 0.4% more increase in capital expenditure. Similar to firm profitability, I cannot find any meaningful dynamic response of firm investment to the productivity shock (column (3) and (4)).

In sum, the results suggest that labor skill dependency amplifies firms' exposure to the technology innovation. Firms that require high degree of labor skills have profits that are more volatile than low skill firms, alongside with aggregate fluctuation. This implies that technology innovation is a economic-wide factor that affect the riskiness of firms.

3.4.3 Labor Skill and the Cross-section of Stock Returns

3.4.3.1 Risk Premia of Technology Shock

Having found that high skill firms have high exposure to the technology shock, it is important to examine its asset pricing implications. High skill firms should have lower expected returns if technology shock is a risk that carry negative risk premia. Even though the seminal work of Papanikolaou (2011) suggest the negative technology risk premia, several recent papers argue the positive risk premia (Li (2014), Garlappi and Song (2016)). For this reason, the discussion regarding the sign of technology risk is needed before investigating the link between labor skill and

[6]The measure of aggregate productivity (TFP, utilization adjusted productivity factor following Basu et al. (2006)) is obtained from Federal Reserve Bank of San Francisco.

asset prices.

In Table 3.5, I first report equal and value-weighted portfolio alphas sorted on β^{IMC}. β^{IMC} is obtained from the equation 3.5 after controlling for market risk factor. I use 36 month rolling window and require stocks to have at least 24 observation in the window. The abnormal returns are obtained from either the Fama-French five factor model (Fama and French (2015)) or the Q-factor model suggested by Hou et al. (2015). The results suggest that technology shock carries a positive risk premia for both returns. High-minus-low portfolio alphas are all positive and large in terms of magnitude. For example, when returns are value-weighted, the IMC premia is 0.78% monthly when Fama-French five factors are used to obtain alphas.

I also directly estimate the IMC risk premia through two-stage Fama-MacBeth regressions. I consider a broad set of test assets, including ten size, ten book-to-market, ten momentum, ten operating profitability, ten investment, and ten portfolios sorted on labor skills. The usage of profitability and investment portfolios are motivated by Fama and French (2015). I also include ten skill portfolios, since the exposure to the technology shock is closely tied to labor skill dependency.

For the first-stage beta regressions, following Liu and Zhang (2008), I estimate portfolio betas with three alternative methods: (i) full-sample window, (ii) rolling five-year windows, and (iii) expanding windows. Using estimated portfolio betas, I report risk premia estimates from the second-stage Fama-MacBeth regressions in Table 3.6. The t-statistics are Newey-West adjusted with sixty month lags. Panel A shows the full-sample window beta results. I find positive and significant IMC estimates in specifications considered. For example, when market risk factor is added to the regression, the IMC risk premia is 0.67% per month with a t-statistic of 2.20. I also find the positive risk premia even after controlling for Fama-French five risk factors.

In Panel B and C, I report the risk premia estimates with alternative first-stage procedures. The results are qualitatively similar albeit weak in terms of significance. In both panels, I find significant IMC risk premia only when all factors are included. Notably, I cannot find any significance for size, book-to-market, and investment factors for all specification considered. In all, I present evidences of positive technology premia as opposed to Papanikolaou (2011).

3.4.3.2 Cross-sectional Analysis

High skill firms are more exposed to technology shock, and hence should have higher expected returns than low skill firms. Using measure of labor skill, I conduct firm-level Fama-MacBeth regression to examine how labor skill is priced in the cross-section.

In Table 3.7, I report estimation results. The variable of interest is *Skill*, which indicates skill intensity measured at industry-level. I also include several characteristics that are known to predict stock returns such as firm size ($size$), logarithm of book-to-market ratio (BM), past 11 month stock return momentum ($R^E_{12,2}$), past 1 month lagged stock return (R^E_1), capital investment (Inv), labor hiring ($Hire$) as in Belo et al. (2014), operating leverage ($Op.Lev$), and book leverage ($Book.$ Lev). I find *Skill* to be positive and significant in most cases. For example, a one-standard-deviation increase in labor skill is associated with 0.25% increase in monthly returns, when all control variables are added. Clearly, high skill firms have subsequent high returns.

I also sort firms according to labor skill and form quintile portfolios. In Table 3.8, I report value-weighted portfolio alphas sorted on labor skill measure. Consistent with Fama-MacBeth results, I find skill premia in the cross-section. For example, high-minus-low five factor alphas are 0.73% monthly.

More importantly, I find that a significant portion of skill premia can be explained by adding technology factor. When portfolio alphas are obtained by adding IMC returns to Fama-French five factors, I find relatively smaller high-minus-low alphas (0.46%). The decrease in alpha is more pronounced when Q-factor model is used to obtain alphas. For example, high-minus-low alphas has decreased almost by half to 0.32% monthly, which is also statistically insignificant. I also report IMC factor loadings in Table 3.8. Regardless of factor model used, I find a increasing pattern of IMC loadings across skill portfolios. Overall, the results suggest the existence of skill premia, which can be partly explained by technology risk exposure.

3.5 Conclusion

This paper provides implication of technology innovation for firm behavior and asset prices, through the labor skill channel. Consistent with the intuition, I find that high skill firms have higher profitability, and increase capital expenditures when positive technology shock arrives, suggesting that high skill firms are more exposed to the shock.

It is still in debate as to the sign of technology risk factor. Contrary to the findings in Papanikolaou (2011), I find positive price of technology risk. This leads to high skill firms to have high subsequent returns. Overall, my findings imply that labor skill mix is an important characteristic, that determine exposure to economic-wide shocks.

3.6 Figures and Tables

Table 3.1 Industry Skill Rankings in 2001

This table presents the top 10 and bottom 10 industries sorted on labor skill measure in 2001. Industry-level labor skill measure is calculated as the proportion of skilled workers in each industry. The number of skilled workers are from the number of workers in occupations that have a Specific Vocational Preparation (SVP) value greater or equal to 7. Labor skill measure is defined at 3-digit SIC level from 1991 to 2001 and at 4-digit NAICS level onwards.

Year	*SIC*	*Skill*	*Description*
2001	172	74.5%	Painting and Paper Hanging (Construction)
2001	376	59.6%	Guided Missiles, Space Vehicles, Parts
2001	821	56.9%	Elementary and Secondary Schools
2001	608	54.5%	Foreign Bank and Branches and Agencies
2001	822	52.5%	Colleges and Universities
⋮	⋮	⋮	⋮
2001	723	1.2%	Beauty Shops
2001	415	1.2%	School Buses
2001	413	0.9%	Intercity and Rural Bus Transportation
2001	076	0.9%	Farm Labor and Management Services
2001	724	0.6%	Barber Shops

Table 3.2 Skill Portfolio Characteristics

This table reports time-series averages of median portfolio characteristics of the quintile portfolios sorted on the labor skill measure. Based on information available at the end of the previous years, in June of each year, I sort stocks into five portfolios using the skill measure. *Skill* is the labor skill measure; *Size* is the log market value of equity; BM is the book-to-market ratio; *Inv* is the capital expenditures-to-assets ratio; *Leverage* is the total book debt divided by the sum of market value of equity and total book debt; $Profit$ is the gross profitability following Novy-Marx (2013); *Cash Flow* is the earnings before extraordinary items plus depreciation to assets ratio; *Labor Share* is the number of employees divided by assets; *Cash* is the ratio of cash and cash equivalent to assets. β^{IMC1} is the stock's IMC beta obtained from the equation 3.4. β^{IMC2} and β^{MKT2} are the stock's IMC beta and market beta obtained by adding market risk factor to the equation 3.4. To estimate betas, I use 36 month rolling window and require stocks to have at least 24 observation in the window. The sample period is from 1991 through 2012.

	L	2	3	4	H
Skill	0.037	0.102	0.172	0.261	0.417
Size	5.335	5.381	5.208	5.131	4.972
BM	0.624	0.595	0.523	0.433	0.448
Inv	0.054	0.040	0.036	0.037	0.036
Book. Lev	0.230	0.229	0.182	0.097	0.065
$Profit$	0.401	0.333	0.278	0.292	0.365
Cash Flow	0.089	0.078	0.059	0.047	0.055
Labor Share	0.011	0.006	0.004	0.004	0.005
Cash	0.055	0.062	0.093	0.248	0.239
β^{IMC1}	0.551	0.686	0.778	1.016	1.020
β^{IMC2}	0.068	0.168	0.320	0.503	0.508
β^{MKT}	0.956	0.982	0.947	1.050	1.041

Table 3.3 Response of Profit to Aggregate Shocks

This table shows the response of firm profit to technology shock for firms in different skill industry. The dependent variable is the gross profitability following Novy-Marx (2013). To proxy for technology shock ($Tech$), I use the innovation in quality-adjusted equipment price relative to consumption. TFP is the aggregate productivity shock following Basu et al. (2006). $Skill$ is the labor skill measure. The sample period is from 1991 through 2012. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. The numbers in parentheses are t-statistics clustered at the firm and year level.

	(1)	(2)	(3)	(4)
$Tech$	0.005**		0.004**	
	(2.24)		(2.18)	
$Tech * Skill$		0.014***		0.016**
		(5.59)		(2.15)
TFP			-0.002	
			(-0.96)	
$TFP * Skill$				0.007
				(0.39)
$Skill$		-0.118		-0.135
		(-1.26)		(-1.16)
Control	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y
Year FE	N	Y	N	Y
Ind*Year FE	Y	Y	Y	Y
Obs	51,592	51,592	51,592	51,592
R^2	78.1%	78.1%	78.1%	78.1%

Table 3.4 Response of Investment to Aggregate Shocks

This table shows the response of firm investment to technology shock for firms in different skill industry. The dependent variable is the capital expenditures to assets ratio. To proxy for technology shock ($Tech$), I use the innovation in quality-adjusted equipment price relative to consumption. TFP is the aggregate productivity shock following Basu et al. (2006). $Skill$ is the labor skill measure. The sample period is from 1991 through 2012. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. The numbers in parentheses are t-statistics clustered at the firm and year level.

	(1)	(2)	(3)	(4)
$Tech$	0.017**		0.017**	
	(2.35)		(2.54)	
$Tech * Skill$		0.028**		0.037**
		(2.16)		(2.25)
TFP			-0.001	
			(-0.19)	
$TFP * Skill$				0.032
				(1.18)
$Skill$		-0.606***		-0.690***
		(-3.98)		(-3.88)
Control	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y
Year FE	N	Y	N	Y
Ind*Year FE	Y	Y	Y	Y
Obs	54,776	54,776	54,776	54,776
R^2	70.9%	70.9%	70.9%	70.9%

Table 3.5 Quintile IMC Beta Portfolio

This table provides average monthly alphas for quintile portfolios sorted on the IMC beta. The IMC beta is obtained by adding market risk factor to the equation 3.4. To estimate beta, I use 36 month rolling window and require stocks to have at least 24 observation in the window. I report equal-weighted alphas (Panel A) and value-weighted alphas (Panel B). Alphas are estimated either from the Fama-French five factor model (Five factors α) or from the Q-factor model (HXZ α). The sample period is from 1991 through 2012. *, **, and *** for the High-Low portfolio alphas denote statistical significance at the 10%, 5%, and 1% levels, respectively. The numbers in parentheses are t-statistics based on White (1980) robust standard errors.

	L	2	3	4	H	High-Low
	Panel A: Equal-Weighted Returns					
Five factors α	0.17	0.13	0.28	0.52	0.70	0.52**
	(1.08)	(1.05)	(2.08)	(2.40)	(2.17)	(2.04)
HXZ α	0.32	0.26	0.43	0.79	1.07	0.75**
	(1.78)	(1.68)	(2.68)	(3.20)	(3.08)	(2.52)
	Panel B: Value-Weighted Returns					
Five factors α	-0.08	-0.13	0.12	0.32	0.70	0.78**
	(-0.83)	(-1.43)	(0.86)	(1.87)	(2.67)	(2.52)
HXZ α	-0.02	-0.13	0.21	0.51	0.78	0.80**
	(-0.21)	(-1.28)	(1.23)	(2.75)	(2.46)	(2.13)

Table 3.6 Risk Premia Estimates

This table reports the estimated IMC risk premia from Fama-MacBeth cross-sectional regressions. The test portfolios are: size deciles, book-to-market deciles, momentum deciles, investment deciles, operating profitability deciles, and skill deciles. I consider both a two-factor model (MKT+IMC) and a six-factor model (FF5+IMC). I employ three methods in the first-stage beta estimation: (1) full-sample window (Panel A); (2) rolling window (Panel B); and (3) extending window (Panel C). The rolling window uses a 5-year moving window. The sample period is from 1991 through 2012. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. The numbers in parentheses are t-statistics based on Newey-West adjusted with a lag of 5 years.

	γ_0	MKT	IMC	SMB	HML	UMD	RMW	CMA	R^2
Panel A: Full-Sample Window in the First-Stage Regression									
MKT+IMC	1.545***	-1.276**	0.670**						20.7%
	(3.51)	(-2.41)	(2.20)						
FF5+IMC	0.855***	-0.289	1.260***	0.394	0.214	0.641*	0.738**	0.100	50.2%
	(3.82)	(-0.74)	(4.14)	(1.20)	(0.58)	(1.92)	(2.38)	(0.31)	
Panel B: Rolling Windows in the First-Stage Regression									
MKT+IMC	0.961***	-0.592	0.451						20.9%
	(3.42)	(-1.28)	(1.30)						
FF5+IMC	0.670***	0.066	0.559**	0.579	0.131	0.921**	0.243	0.240	47.2%
	(3.45)	(0.15)	(2.13)	(1.13)	(0.38)	(2.21)	(0.44)	(0.65)	
Panel C: Extending Windows in the First-Stage Regression									
MKT+IMC	0.988**	-0.454	0.133						18.8%
	(2.04)	(-0.72)	(0.36)						
FF5+IMC	0.566**	0.256	0.847***	0.583	-0.011	0.778**	0.681*	0.230	46.5%
	(2.47)	(0.88)	(3.15)	(1.36)	(-0.03)	(2.32)	(1.97)	(0.73)	

Table 3.7 Fama-MacBeth Regression

This table provides the second stage Fama-MacBeth regressions of monthly excess stock returns on the labor skill (*Skill*) along with a set of controls. *Skill* is the labor skill measure; *Size* is log market capitalization; *BM* is the log book-to-market ratio; $R^E_{2,12}$ is the past 12 month stock return skipping the most recent month; R^E_1 is the past 1 month stock return; *Inv* is the capital expenditures to assets ratio; *Hire* is the change in number of employees divided by lagged number of employees; *Op. Lev* is the sum of cost of goods sold and selling, general and administrative expenditures, divided by sales; *Book. Lev* is the total book debt divided by the sum of market value of equity and total book debt. The sample period is from 1991 through 2012. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. The numbers in parentheses are t-statistics based on the White (1980) standard errors.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Skill	1.675*	1.562	2.167**	1.640*	1.731*	1.638*	1.821*	1.828**	1.493*	1.767***
	(1.72)	(1.61)	(2.50)	(1.94)	(1.96)	(1.69)	(1.95)	(2.00)	(1.72)	(2.79)
Size		-0.153**								-0.099
		(-2.14)								(-1.64)
BM			0.436***							0.268***
			(5.14)							(3.48)
$R^E_{12,2}$				0.001						0.002
				(0.52)						(0.93)
R^E_1					-0.032***					-0.035***
					(-4.21)					(-5.69)
Inv						-1.388*				-0.313
						(-1.69)				(-0.36)
Hire							-0.848***			-0.617***
							(-6.13)			(-4.95)
Op. Lev								-0.211*		-0.231**
								(-1.66)		(-2.23)
Book. Lev									0.008	-0.037
									(0.19)	(-1.16)
R^2	0.69%	1.60%	1.20%	1.61%	1.51%	0.91%	0.94%	1.30%	0.87%	4.67%
Obs	896,457	896,357	822,589	885,908	896,297	878,889	846,731	803,346	752,126	578,061

Table 3.8 Quintile Skill Portfolio

This table provides average value-weighted monthly alphas and IMC factor loadings for quintile portfolios sorted on the labor skill. Alphas are estimated either from the Fama-French five factor model (Panel A) or from the Q-factor model (Panel B). For each panel, I also report portfolio alphas and IMC factor loadings, both obtained from adding IMC factor to the original model considered. The sample period is from 1991 through 2012. *, **, and *** for the High-Low portfolio alphas denote statistical significance at the 10%, 5%, and 1% levels, respectively. The numbers in parentheses are t-statistics based on White (1980) robust standard errors.

	L	2	3	4	H	High-Low
	Panel A: Fama-French Five Factors					
Five factors α	-0.27	-0.10	-0.18	0.32	0.45	0.73***
	(-2.18)	(-0.97)	(-1.29)	(2.51)	(2.74)	(3.22)
Five+IMC α	-0.19	-0.09	-0.19	0.22	0.27	0.46**
	(-1.57)	(-0.83)	(-1.35)	(1.84)	(1.93)	(2.46)
IMC Loading	-0.22	-0.04	0.03	0.23	0.45	0.67***
	(-4.93)	(-1.05)	(0.44)	(4.52)	(8.92)	(10.45)
	Panel B: HXZ Q-Factors					
HXZ α	-0.15	-0.12	-0.08	0.29	0.55	0.70**
	(-0.89)	(-1.05)	(-0.55)	(2.07)	(3.07)	(2.56)
HXZ+IMC α	0.01	-0.06	-0.07	0.14	0.33	0.32
	(0.05)	(-0.51)	(-0.44)	(1.11)	(2.23)	(1.54)
IMC Loading	-0.34	-0.13	-0.03	0.31	0.48	0.81***
	(-7.24)	(-3.39)	(-0.56)	(5.88)	(10.88)	(12.97)

APPENDIX A

NUMERICAL ALGORITHM

All endogenous variables in the model are functions of the state variables. The model is solved numerically at a monthly frequency, which is the frequency of the stock return data used in the empirical tests.

I use the value function iteration procedure to solve the firm's maximization problem. The value function and the optimal decision rule are solved on a grid in a discrete state space. I specify a grid of 27 points for capital and labor, respectively, with upper bounds that are large enough to be nonbinding. The grids for capital and labor stocks are constructed recursively, following McGrattan (1999). The advantage of this recursive construction is that more grid points are assigned around where the value function has most of its curvature. The aggregate productivity shock is an i.i.d. standard normal shock. I discretize into 5 grid points using Gauss-Hermite quadrature. The state variables s and z have continuous support in the theoretical model, but they have to be transformed into discrete state space for the numerical implementation. I use the method described in Rouwenhorst (1995) for a quadrature of the Gaussian shocks. I use 9 grid points for the s process and 5 grid points for the z process. Once the discrete state space is available, the conditional expectation can be carried out simply as a matrix multiplication. Cubic spline interpolation is used extensively to obtain optimal investment and hiring that do not lie directly on the grid points. Finally, I use a simple discrete global search routine in maximizing the firm's problem.

APPENDIX B

INDUSTRY CLASSIFICATION

Table B.1 Industry Classification

Number	Industry Description	IND1990 Code
1	Metal mining	40
2	Coal mining	41
3	Oil and gas extraction	42
4	Nonmetallic mining and quarrying, except fuels	50
5	Construction	60
6	Food and kindred products	100 - 122
7	Tobacco manufactures	130
8	Textile mill products	132 - 150
9	Apparel and other finished textile products	151 - 152
10	Paper and allied products	160 - 162
11	Printing, publishing, and allied industries	171 - 172
12	Chemicals and allied products	180 - 192
13	Petroleum and coal products	200 - 201
14	Rubber and miscellaneous plastics products	210 - 212
15	Leather and leather products	220 - 222
16	Lumber and woods products, except furniture	230 - 241
17	Furniture and fixtures	242
18	Stone, clay, glass, and concrete products	250 - 262
19	Metal industries	270 - 301
20	Machinery and computing equipments	310 - 332
21	Electrical machinery, equipment, and supplies	340 - 350
22	Motor vehicles and motor vehicle equipment	351
23	Other transportation equipment	352 - 370
24	Professional and photographic equipment and watches	371 - 381
25	Miscellaneous manufacturing / Toys, amusement, and sporting goods	390 - 392
26	Railroads	400
27	Bus service and urban transit / Taxicab service	401 - 402
28	Trucking service / Warehousing and storage	410 - 411
29	U.S. postal service	412
30	Water transportation	420

Table B.1 (con't.)

Number	Industry Description	IND1990 Code
31	Air transportation	421
32	Pipe lines, except natural gas / Services incidental to transportation	422 - 432
33	Communications	440 - 442
34	Utilities and sanitary services	450 - 472
35	Durable goods	500 - 532
36	Nondurable goods	540 - 571
37	Lumber and building material retailing	580
38	General merchandiser	581 - 600
39	Food retail	601 - 611
40	Motor vehicle and gas retail	612 - 622
41	Apparel and shoe	623 - 630
42	Furniture and appliance	631 - 640
43	Eating and drinking	641 - 650
44	Miscellaneous retail	651 - 691
45	Banking and credit	700 - 702
46	Security, commodity brokerage, and investment companies	710
47	Insurance	711
48	Real estate, including real estate-insurance offices	712
49	Business services	721 - 741
50	Automotive services	742 - 751
51	Miscellaneous repair services	752 - 760
52	Hotels and lodging places	761 - 770
53	Personal services	771 - 791
54	Entertainment and recreation services	800 - 810
55	Health care	812 - 840
56	Legal services	841
57	Education services	842 - 861
58	Miscellaneous services	862 - 881
59	Professional services	882 - 893
60	Public administration	900 - 932

APPENDIX C

EVIDENCE FROM MARCH CPS

The census data that I used in the main tests are published once a decade. Although I show the persistence of wage premia for decades, data frequency can be an issue. To obtain industry wage premia at a higher frequency, I exploit the March Current Population Survey (CPS) data and repeat the cross-sectional analyses in Section 1.3.

One drawback of March CPS is the small number of observations relative to the decennial census data, which may cause noise in wage premia estimates. To avoid this problem, I may reclassify industries into a small number of groups to assign a higher number of observations in each industry. For example, I can regroup the railroad industry and the bus/taxicab service industry into a single transportation category. However, the new classification raises a problem because it may attenuate the heterogeneity between industries. For example, wage premia for railroads show the highest wage level in 1980, whereas the bus/taxicab service industry ranked 39th. Because the heterogeneity between a firm's labor cost is a key feature in the analysis, I follow the same industry classification rule described in Appendix B.

Table C.1 documents wage premia estimation results using the March CPS. I also compare wage rankings with those of the census data to examine whether the estimates are consistent between two sources of data. In Table C.1, I report the 10 highest and lowest wage premia industries in 2010 and their rankings in the census data (shown in the parentheses). Among high wage firms, some industries show gaps between two rankings. For example, the banking and credit related industry is ranked 23rd in the census data and 5th in the March CPS. The estimates for low wage firms seem more aligned with those from the census. In both datasets, the lowest wage industries are the miscellaneous retail and apparel and shoe industries. From a comparison between two rankings, I may conclude that estimates from the March CPS are not severely biased.

Given the estimated wage premia from the March CPS, I first conduct portfolio sorting. Similar to Table 1.8, I form two decile portfolios double sorted on wage and investment. At the end of June of each year, firms are sorted into two wage portfolios using the wage premia for the year. Additionally, firms are independently grouped into ten investment portfolios using NYSE breakpoints. I form both equal- and value-weighted portfolios of monthly stock returns, and they are rebalanced in June of each year. Table C.2 provides the average returns and alphas for double sorted portfolios. The sample starts from 1971 and goes to 2014 given data limitations. I report low, high, and high-minus-low investment portfolios in each wage bin. In Panel A, for which returns are equal-weighted, I find that the results are consistent with the results in Table 1.8. For example, when $IA1$ is the sorting variable, the monthly high-minus-low return is -1.07% for high wage industries and -0.77% for low wage industries. When returns are value-weighted, I only find $IA1$ results to be significant.

I also conduct Fama-MacBeth regressions to control for other characteristics that might affect a cross-section of stocks. I use the same control variables as in the main tests. The variable of interest is the interaction between investment and wage premia ($IA * Wage$). Table C.3 presents the Fama-MacBeth regression results. Consistent with the census results, I find steeper investment-return relations for industries paying high wage premia, meaning that the estimated investment-wage interaction term is significantly negative. When $IA1$ is used to proxy firm investment, the interaction variable is significant at the 5% or 10% level based on the specification. This variable is large in terms of economic magnitude. For example, the estimate for the investment-wage term is -0.89 after controlling for size, book-to-market, momentum, and reversal. This implies that a one-standard-deviation increase in wages (0.3) is associated with a 0.27% greater decrease in monthly returns for a typical increase in investments. From columns (4) to (6), I document the asset growth results. Overall, the asset growth effect is closely tied to the wage level. I find a significant interaction term at 5% for all specifications considered. However, when $IA3$ is used as the main regressor, the interaction terms become marginally significant.

In sum, I draw the same conclusion as the main result that high wage industries show larger investment spreads than low wage industries. However, because the wage premia estimates from the March CPS are noisy, I obtain relatively weaker results compared with the census results.

Table C.1 Industries with Highest and Lowest Wage Premia: March CPS

This table presents the 10 industries with the highest and lowest values of wage premia from the March CPS. Industry wage premia is the estimated from the regression (1.1). Industries are classified into 60 categories described in Appnedix B. Numbers in parentheses indicate wage premia rankings from the Census data in 2010.

Rank	Industry	Wage Premia
	Panel A: Ten Industries with Highest Wage Premia	
1	Water transportation (7)	0.86
2	Railroads (2)	0.83
3	Metal mining (4)	0.83
4	Coal mining (1)	0.82
5	Banking and credit (23)	0.69
6	Oil and gas extraction (5)	0.68
7	Nonmetallic mining and quarrying, except fuels (19)	0.66
8	U.S. postal service (9)	0.66
9	Security, commodity brokerage, and investment companies (8)	0.59
10	Paper and allied products (11)	0.58
	Panel B: Ten Industries with Lowest Wage Premia	
51	Furniture and appliance (45)	0.12
52	Education services (51)	0.08
53	Miscellaneous services (55)	0.00
54	Hotels and lodging places (54)	0.00
55	Food retail (53)	0.00
56	Eating and drinking (56)	-0.01
57	General merchandiser (57)	-0.02
58	Entertainment and recreation services (58)	-0.04
59	Miscellaneous retail (59)	-0.06
60	Apparel and shoe (60)	-0.18

Table C.2 Two-way Sorts on Wage and Capital Investment: March CPS

This table provides average monthly returns and alphas for low, high, and high-minus-low portfolios double sorted on industry wage premia and investment variables. Industry wage premia is estimated using the March CPS data. The sorting variables are investment-to-assets ($IA1$), asset growth ($IA2$), and capital expenditures divided by property, plant and equipment ($IA3$). Based on information available at the end of the previous years, I sort stocks into two groups using estimated wage premia. Meanwhile, independently, firms are grouped into decile portfolios based on the NYSE breakpoints of investment variable. I form equal-weighted (Panel A) and value-weighted (Panel B) portfolios in June of each year. Alphas are estimated from the Fama-French three factor model. The sample period is from 1971 through 2014. *, **, and *** for the High-Low portfolio alphas denote statistical significance at the 10%, 5%, and 1% levels, respectively. The numbers in parentheses are t-statistics based on White (1980) robust standard errors.

		Low	High	High-Low	Low	High	High-Low	Low	High	High-Low
		Panel A : Equal-Weighted Returns								
		$IA1$			$IA2$			$IA3$		
Excess Returns	Low Wage	0.91	0.15	-0.77***	1.06	0.15	-0.92***	0.97	0.47	-0.49***
		(2.94)	(0.45)	(-6.09)	(3.05)	(0.43)	(-6.53)	(3.34)	(1.42)	(-3.57)
	High Wage	1.27	0.20	-1.07***	1.27	0.26	-1.01***	1.16	0.48	-0.68***
		(3.73)	(0.58)	(-7.17)	(3.41)	(0.75)	(-7.11)	(3.66)	(1.30)	(-4.57)
	Difference			-0.30**			-0.09			-0.19
				(-2.09)			(-0.79)			(-1.50)
Fama-French α	Low Wage	-0.03	-0.71	-0.68***	0.13	-0.63	-0.75***	0.05	-0.30	-0.35***
		(-0.21)	(-4.83)	(-5.71)	(0.79)	(-4.15)	(-6.03)	(0.42)	(-2.27)	(-3.48)
	High Wage	0.36	-0.66	-1.03***	0.37	-0.50	-0.87***	0.30	-0.26	-0.55***
		(2.35)	(-4.02)	(-7.17)	(2.01)	(-3.47)	(-6.60)	(2.05)	(-1.72)	(-4.59)
	Difference			-0.34**			-0.11			-0.20
				(-2.36)			(-0.96)			(-1.63)
		Panel B : Value-Weighted Returns								
		$IA1$			$IA2$			$IA3$		
Excess Returns	Low Wage	0.84	0.38	-0.46**	0.94	0.39	-0.55**	0.80	0.51	-0.29
		(3.20)	(1.27)	(-2.41)	(3.34)	(1.26)	(-2.56)	(3.20)	(1.63)	(-1.31)
	High Wage	0.93	0.25	-0.68***	0.77	0.36	-0.41**	0.67	0.42	-0.26
		(3.54)	(0.87)	(-3.97)	(2.84)	(1.24)	(-2.40)	(2.61)	(1.24)	(-1.07)
	Difference			-0.22			0.14			0.03
				(-0.95)			(0.62)			(0.14)
Fama-French α	Low Wage	0.04	-0.23	-0.27	0.12	-0.06	-0.17	0.02	0.05	0.03
		(0.33)	(-1.60)	(-1.49)	(0.81)	(-0.47)	(-0.88)	(0.18)	(0.41)	(0.17)
	High Wage	0.22	-0.33	-0.56***	0.02	-0.14	-0.16	-0.06	-0.01	0.06
		(1.77)	(-2.44)	(-3.16)	(0.13)	(-1.27)	(-1.03)	(-0.49)	(-0.05)	(0.28)
	Difference			-0.29			0.01			0.03
				(-1.14)			(0.06)			(0.11)

Table C.3 Fama-MacBeth Regressions: March CPS

This table provides the second stage Fama-MacBeth regressions of monthly excess stock returns on the investment (IA), wage premia ($Wage$), and the interaction term between investment and wage premia ($IA * Wage$) along with a set of controls. I use investment-to-assets ($IA1$) to proxy for firm investment from column (1) to (3), asset growth ($IA2$) from column (4) to (6), and capital expenditures divided by property, plant and equipment ($IA3$) from column (7) to (9). $Wage$ is the wage premia estimated in equation (1.1), using the March CPS data. *Size* is log market capitalization; $log(BM)$ is the log book-to-market ratio; $R^E_{2,12}$ is the past 12 month stock return skipping the most recent month; R^E_1 is the past 1 month stock return; $Hire$ is the change in number of employees divided by lagged number of employees; $Idiosyn$ is the idiosyncratic risk computed as the logistic transformation of the coefficient of determination from a regression of daily excess returns on the Fama-French three factor model; $Mkt.\ Lev$ is the total book debt divided by the sum of market value of equity and total book debt; *Cash Flow* is the earnings before extraordinary items plus depreciation divided by capital stock. The sample period is from 1971 through 2014. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. *Avg Obs* is the average firm-month observation in the sample. The numbers in parentheses are t-statistics based on the White (1980) standard errors.

	$IA1$			$IA2$			$IA3$		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
IA	-1.066***	-0.665***	-0.390*	-0.391***	-0.296***	-0.311***	-0.332***	-0.175*	-0.103
	(-4.35)	(-2.98)	(-1.71)	(-3.72)	(-3.02)	(-2.80)	(-3.40)	(-1.95)	(-1.01)
$IA * Wage$	-0.689*	-0.890**	-0.992**	-0.354**	-0.320**	-0.365*	-0.197	-0.261*	-0.285
	(-1.72)	(-2.29)	(-2.46)	(-2.18)	(-1.99)	(-1.96)	(-1.22)	(-1.70)	(-1.61)
$Wage$	0.192	0.295**	0.294**	0.156	0.244*	0.239*	0.139	0.265*	0.246*
	(1.32)	(2.27)	(2.32)	(1.03)	(1.80)	(1.76)	(0.94)	(1.96)	(1.84)
Size		-0.072	-0.098**		-0.074*	-0.097**		-0.081*	-0.102**
		(-1.62)	(-2.31)		(-1.66)	(-2.30)		(-1.85)	(-2.44)
$log(BM)$		0.324***	0.321***		0.314***	0.322***		0.321***	0.327***
		(4.98)	(5.89)		(5.00)	(5.96)		(5.17)	(6.05)
$R^E_{2,12}$		0.005***	0.005***		0.005***	0.005***		0.005***	0.005***
		(3.13)	(3.21)		(3.17)	(3.21)		(3.27)	(3.26)
R^E_1		-0.060***	-0.057***		-0.060***	-0.057***		-0.059***	-0.057***
		(-14.00)	(-13.70)		(-14.06)	(-13.67)		(-13.93)	(-13.57)
$Hire$			-0.207***			-0.175**			-0.386***
			(-2.60)			(-2.29)			(-5.22)
$Idiosyn$			-0.155***			-0.157***			-0.156***
			(-4.22)			(-4.27)			(-4.26)
$Mkt.\ Lev$			-0.035			-0.045**			-0.047**
			(-1.54)			(-2.02)			(-2.11)
Cash Flow			-0.004			-0.003			-0.003
			(-0.24)			(-0.20)			(-0.19)
Avg R^2	0.75%	4.06%	5.08%	0.82%	4.08%	5.06%	0.86%	4.08%	5.06%
Avg Obs	3,102	2,868	2,363	3,139	2,901	2,385	3,098	2,865	2,365

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